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Climate change and its weather hazard on the reliability of railway infrastructure

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Due to the accumulated greenhouse gas (GHG) effect, climate change will affect infrastructure networks regardless of different climate mitigation strategies. Our current investigation reveals an apparent increasing trend in the number of climatic-based failures in the Swedish railway infrastructure from 2010 until 2020.
Switch and crossing (S&C) is a critical part of the railway infrastructure network, which plays a key role in adjusting the railway network capacity and dependability performance. Due to the structure of S&C, it can be affected more by extreme climate change impacts, e.g., abnormal temperature, ice and snow, and flooding. Clearly, the reliability and hazard function of infrastructures will be affected by age and environmental conditions. Therefore, it is essential to analyze the effect of different climate change features / explanatory variables called "covariates" on the reliability of S&Cs. The proportional hazard model (PHM) is a practical approach to assess and prioritize the impact of various environmental covariates on S&Cs' reliability.
This paper aims to integrate climate change data with infrastructure asset health. This integration can be developed by utilizing proportional hazard methodology to assess the effect of different covariates on the reliability function. The proposed methodology has been verified through a number of S&Cs located on the Swedish railway network. As a main result, this study has revealed that the operational environment covariates significantly influence the reliability of S&Cs and profoundly affect the availability and capacity of railway tracks. The study indicates the need for effective climate adaptation options to reduce climate change impacts and risks to achieve resilience and climate-neutral railway infrastructure asset.

Keywords: Railway infrastructure, Cox proportional hazard model, Reliability analysis, climate change, climate adaptation.

1. Introduction

The railway network can be described as a "system of systems" where various sub-systems work together to enable the transportation of people and goods as a whole. This demand is increasing globally and locally, while the industry faces economic and performance pressures that make it more challenging to maintain sustainability and availability. On the other hand, climate change consequences include heatwaves, flooding, rising sea levels, and severe snow falling and coldness, ultimately leading to reduced availability, safety, and punctuality and increased operation and maintenance costs (Thaduri et al. 2021, Garmabaki et al. 2021, Garmabaki et al. 2022).

It is vital to consider different operational factors affecting the system's behavior (Gao, Barabady, and Markeset 2010, Barabadi, Barabady, and Markeset 2011). The study by (Thijssens and Verhagen 2020) evaluates the use of an extended Cox regression model in analyzing time-on-wing data of aircraft components, finding that it provides a more accurate prediction of time-to-failure than traditional survival analysis methods. The model can also effectively account for the effects of various factors on the time-to-failure of components, such as operating conditions, maintenance actions, and design characteristics. The study also suggests that aircraft components installed in hot desert climates have better reliability than those in humid climates.

In another study, Barabadi, Barabady, and Markeset (2014) used the Proportional Hazards Model (PHM) to predict and optimize spare parts requirements. The PHM was used to model the failure rate of spare parts based on covariates such as operating hours and usage history. The study provides a methodology for using reliability models with covariates in practice and shows results demonstrating their usefulness in predicting spare parts requirements.

Liu et al. (2020) used proportional hazards models to develop a maintenance strategy that considers system components' aging and cumulative damage. Through simulations and case studies, the authors showed that this approach can effectively predict maintenance needs and improve system reliability. (Chen et al. 2020) used a Cox proportional hazard deep learning model for predictive maintenance. The model combines the Cox proportional hazard model with deep learning techniques called Cox proportional hazards deep learning (CoxPHDL) to improve the accuracy of maintenance predictions. The deep learning part is used to model the complex relationship between predictors and the failure times, while the Cox model part allows for handling data censoring. (Zheng et al. 2021) proposed a proportional hazard model incorporating degradation trends and environmental factors to predict product reliability. The authors conducted a case study using a real-world dataset and modelled degradation using the Wiener process. The research suggests that considering degradation trends and environmental factors can improve the accuracy of reliability predictions and provide helpful information for product reliability management.

This paper aims to integrate meteorological factors like temperature, precipitation, snow speed, and humidity with railway infrastructure asset health. This approach will be used to analyze the effect of these parameters on hazard rate/reliability and assess the impact of various scenarios on the failures of railway assets. The rest of this paper is organized as follows: in Section 2, the Cox model and paper's methodology are described, and in section 3 case study and related data are presented. Results will be discussed in section 4, and finally, conclusion and more study will be presented.

2. Methodology of the study

2.1. Methodology

Figure 1 shows the process proposed in this paper, including 4 phases.

2.1.1. Phase 0, data gathering

Switches and crossings (S&C) with the highest failure frequency at different railway stations were selected as use cases. Data from various sources, including the Swedish Meteorological and Hydrology Institute (SMHI) and the Trafikverket failure database (Ofelia) and the asset registry database (BIS), were collected in phase zero. The nearest weather stations to the railway stations were identified, and meteorological parameters were extracted. The combination of SMHI and TRV (Trafikverket/ Swedish Transport Administration), VViS (Swedish Transport Administration's weather information) databases allowed for precisely determining failure time and meteorological parameters. The failures were categorized into climatic and non-climatic failures, with climatic failures being those caused by weather or meteorological factors.

2.1.2. Phase 1, failure trend assessment

During this stage, the failure times that have been extracted are evaluated to determine the Independent and Identically Distributed (IID) using statistical or graphical methods. This test helps determine the behavior of the baseline hazard, which will be discussed in the Cox model section.

2.1.3. Phase 2, Cox model development

Cox (1972) developed the proportional hazard model (PHM); the Cox PH model is usually written in terms of the hazard model formula shown in Equation (1). This model expresses the hazard at time t for an individual with a given specification of a set of explanatory variables denoted by $\boldsymbol{X}$. The $\boldsymbol{X}$ represents a collection (sometimes called a "vector") of predictor variables being modeled to predict an individual's hazard. The Cox model formula says that the hazard at time t is the product of two quantities. The first of these $h_0(t)$, is called the baseline hazard function. The second quantity is the exponential expression e to the linear sum of $\beta_i X_i$, where the sum is over the p explanatory X variables (Kleinbaum and Klein 1996).

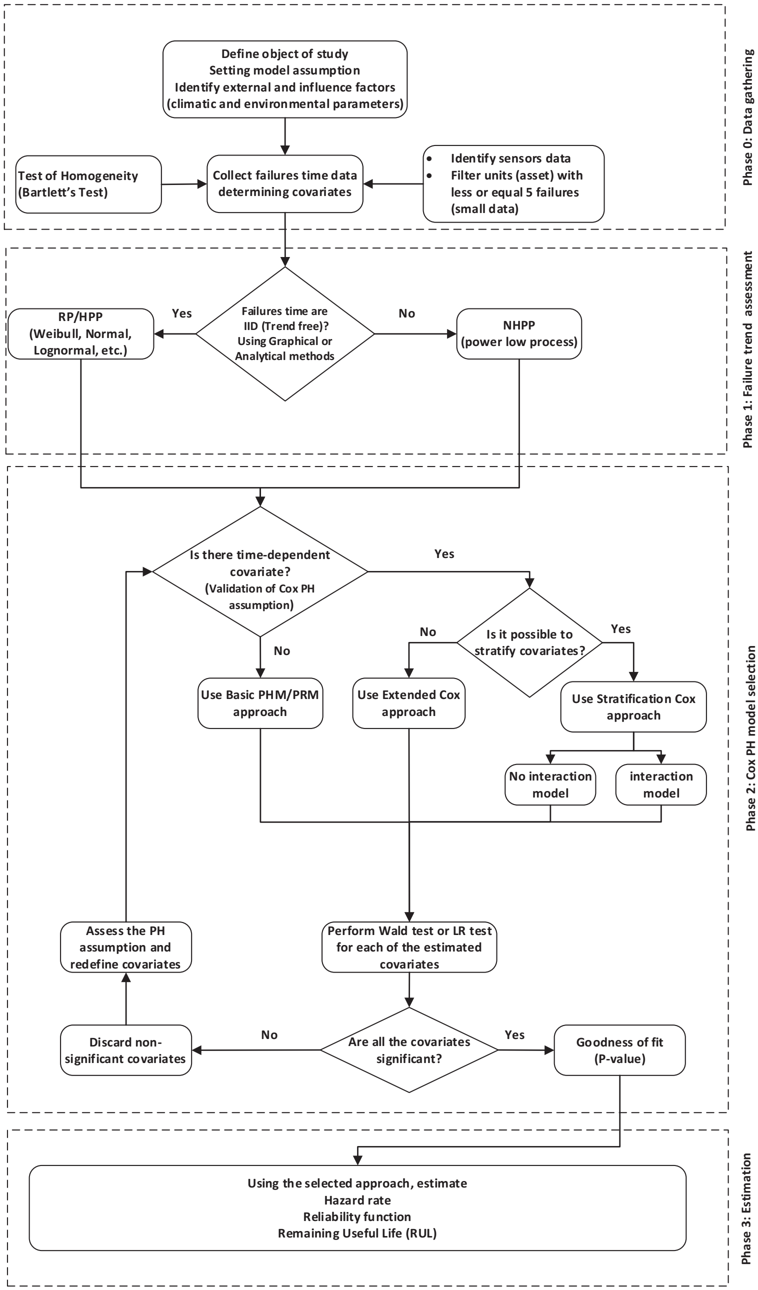


Figure 1. A holistic framework for Cox PH model implementation

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

A hazard ratio (HR) is the hazard for one individual divided by the hazard for a different individual. The two individuals being compared can be distinguished by their values for the set of predictors, X's. The HR can be written as the estimate of $h(t, \boldsymbol{X_1})$ divided by the estimate of $h(t, \boldsymbol{X_2})$ where $h(t, \boldsymbol{X_1})$ denotes the set of predictors for one individual, and $h(t, \boldsymbol{X_2})$ for the other individual. The HR is independent of t, and the result equals a constant value (See Equation 2). This equation is a mathematical expression that states the PH assumption. There are two options when the PH assumption is not satisfied: a stratified Cox model (SCM) or an extended Cox model (ECM).

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

2.1.4.Phase 3, Estimation

Based on previous phases, the impact of various covariates on the hazard function and reliability function needs to be assessed. Furthermore, sensitivity analysis can be performed to evaluate the potential impact of different climate change scenarios on railway infrastructure asset health. By examining different climate change scenarios for the future, it is possible to gain insight into how asset health may be impacted in the long term. This information can be valuable for decision-makers in developing effective maintenance strategies for infrastructure assets ensuring the safe and reliable operation of the railway system.

3. Case study

Switches and crossings (S&Cs), also known as turnouts or points, are critical components of railway engineering that enable trains to change tracks. They are made up of two main parts, the switch, and the crossing, which work together to guide trains from one track to another. The selection and usage of S&Cs depend on the railway system's design and operational requirements. They are commonly used in complex areas of the railway network, such as junctions, terminals, and marshaling yards, where multiple trains must be directed to different tracks. After pre-processing of TRV datasets and merging them with meteorological data, as illustrated in Figure 2, the dataset required for Cox model analyses is prepared.

Table 1 presents the specifications of the five selected assets and failures and meteorological data were collected for a duration of 18 years, ranging from 2001 to 2018 for them.

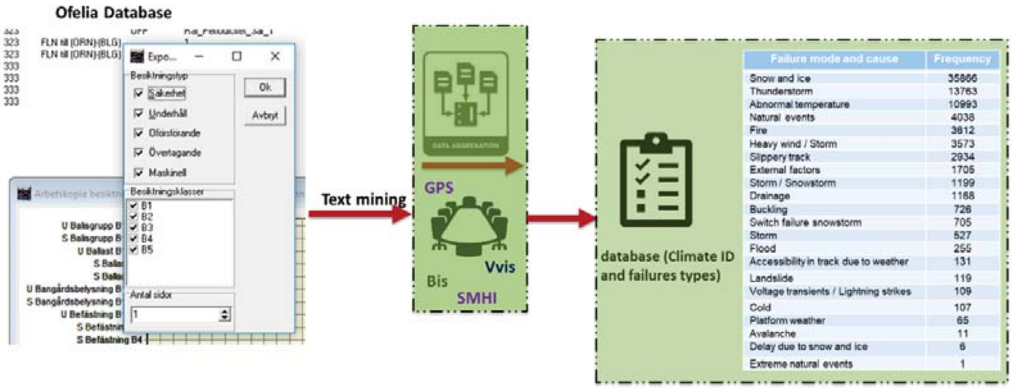
4. Result and discussion

Trend analysis is a statistical method commonly utilized in investigating changes in the operation of a repairable unit over time. The pattern of failures can either be monotonic or non-monotonic. In the case of a monotonic trend, the system has a concave or convex shape. Non-monotonic trends occur when trends change with time or repeat themselves in cycles. Several trend tests are widely used in reliability studies, including the Laplace trend test, Military Handbook test, and Anderson-Darling test, which are described in various sources such as (Garmabaki et al. 2016, Ascher and Feingold 1984, Viertävä and Vaurio 2009).

Table 1.Assets' ID and their locations

Object ID	Region	Latitude	Longitude
200020	Gothenburg	57.71038	11.98253
200026	Gothenburg	57.71051	11.98274
3860099	Luleå	65.58089	22.16984
2960022	Kiruna	67.86347	20.20417
20021	Borlänge	60.47647	15.41973

In the considered statistical analysis, the null hypothesis in trend tests asserts the absence of any significant pattern or trend in the data under analysis. Based on the statistical analysis, the results confirm that the null hypothesis is rejected for all tests. The results of the graphical trend analysis are shown in Figure 3, indicating the presence of a trend in the data for both individual assets and the group of assets as a whole (integrated scenbario). In addition, Figure 3 a and b show the estimated and actual values of the number of faults over operation time.

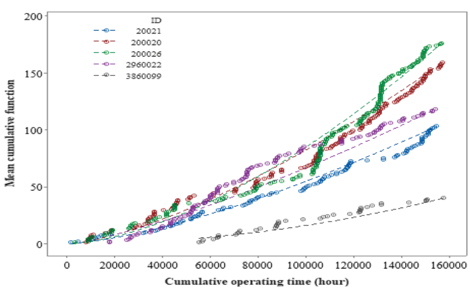


Failure mode and cause	Frequency
Snow and ice	35866
Thunderstorm	13763
Abnormal temperature	10993
Natural events	4038
Fire	3612
Heavy wind / Storm	3573
Slippery track	2934
External factors	1705
Storm / Snowstorm	1199
Drainage	1168
Buckling	726
Switch failure snowstorm	705
Storm	527
Flood	255
Accessibility in track due to weather	131
Landslide	119
Voltage transients / Lightning strikes	109
Cold	107
Platform weather	65
Avalanche	11
Delay due to snow and ice	6
Extreme natural events	1

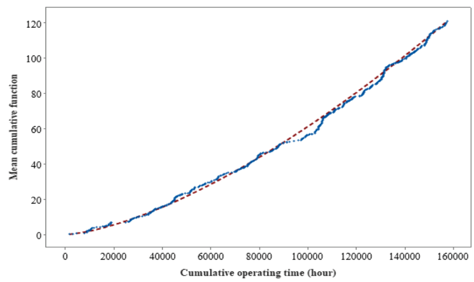
Figure 2. Analyzing the data and deriving different failure modes

Cox model development needs to be developed at this stage. For this purpose, hourly explanatory variables (covariates) including temperature, humidity, precipitation, and wind speed have been selected. It should be considered that selected covariates have a gradual effect, not instantly; therefore, for covering the meteorological effects, the average hourly value of covariates during the 24 hours prior to the failures are considered as input in the Cox PH model.

STATA 15 software is used to assess Andersen-Gill model parameters. t. The coefficients of the covariates (β_i), and HR are shown in Table 2. The null hypothesis in the AG model is that the covariate has no significant effect on the hazard ratio. Therefore, the P-values reject the null hypothesis for the whole of the covariates in as shown in Table 2.



(a)



(b)

Figure 3. Trend behaviour of the assets with the deteriorating trend, (a) each S&C analyzed separately, (b) whole assets analyzed as one group (integrated scenario)

The resulting coefficients of the covariates (β_i), and hazard ratios are presented in Table 2. The null hypothesis assumes that the covariates have no significant effect on the hazard ratio. Therefore, the P-values obtained from the model reject the null hypothesis for all covariates, except humidity (See Table 2) which results in omitting the humidity parameter and rerunning the model again.

Table 2. Results of the Cox PH model

Covariate	Coef. β_i	HR	Robust Std. Err.	P-value
Temperature (T)	-0.05	0.95	0.0075	0.00
Humidity (H)	0.02	1.02	0.0151	0.16
Precipitation (P)	1.49	4.44	0.3424	0.00
Wind speed (W)	-0.09	0.91	0.0455	0.05

After dropping the Humidity parameter and rerunning the model the details of model parameters can be found as per Table 3,

Table 3. Results of the Cox PH model after dropping Humidity parameter

Covariate	Coef. β_i	HR	Robust Std. Err.	P-value
Temperature (T)	-0.05	0.95	0.0075	0.00
Precipitation (P)	1.94	6.96	0.3424	0.00
Wind speed (W)	-0.09	0.91	0.0455	0.03

Schoenfeld results for test of proportional-hazards assumption is used, the null hypothesis for this test states that there is no time dependency for the parameter, and it is clear in Table 4.

Table 4. Schoenfeld results for test of proportional hazards assumption

Covariate	P-value
Temperature (T)	0.85
Precipitation (P)	0.74
Wind speed (W)	0.23

Hazard rate formula are shown in Equation (3)

$$h(t, \boldsymbol{X}) = h_0(t)\exp\left(-0.05\mathrm{T} + 1.94\mathrm{P} - 0.09\mathrm{W}\right) \qquad (3)$$

The way to interpret this output is by looking at the e^{β_i} values. A value of coefficient less than 1 says that an increase in one unit, will decrease the probability of experiencing an event throughout the observation period. By inverting (that is $1/e^{\beta_i}$), the "protective effect" will be found. For temperature parameter (T), $exp(\beta_T = -0.05)$=0.95 and 1/0.95=1.05; the interpretation will be that having the one-unit increase means that the asset will be experienced 1.05 less the probability of experiencing an event. The same interpretation can be presented for the Wind speed (W) parameter, $exp(\beta_W = -0.09)$ = 0.91 and 1/0.91=1.10, which means one unit increase in wind speed value decreases the probability of experiencing failure 1.10 times. For $exp\beta_i > 1$, the interpretation is easier; for precipitation (P), the $exp(\beta_P = 1.94)$ =6.96, which means that one unit increase in precipitation value results in about seven times more possibility of experiencing the desired failure.
In Figure 4, the reliability/survival probability is shown, and as it can be concluded, the system after operating for 10,000 hours, approximately 42 percent is expected to still be functioning or in a reliable state, while the remaining 58 percent may have experienced failures or become unreliable.

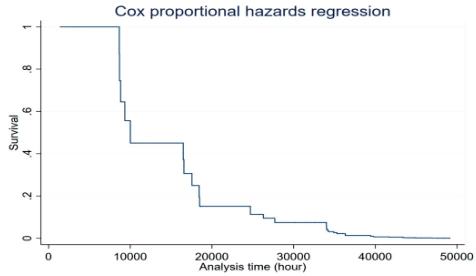


Figure 4. Probability of survival analysis graph (at the mean value of the covariates)

In Figure 5, the cumulative hazard for different values of precipitation are shown, it is clear that increasing this parameter significantly can affect the failure rate, as an consequence of climate change the severity of precipitation will be increase and the failures behaviour will tend towards the redline, which leads to more failures frequency.

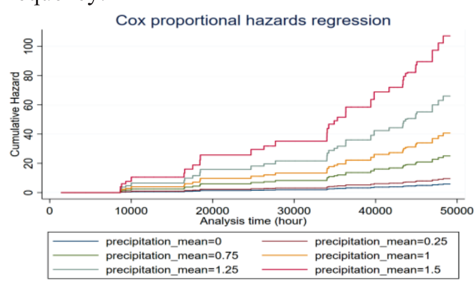


Figure 5. Cumulative hazard rate for different precipitation values

5. Conclusion

In this study, we investigated the impact of climate change on the reliability of railway infrastructure by considering the effects of temperature, humidity, wind speed, and precipitation as covariates. After conducting a thorough analysis using Stata software, we found that humidity did not have a significant effect on the hazard rate function. However, we found that precipitation had a significant effect on the hazard function. The result reveal that the impact of climate change and the changing values of precipitation can greatly impact the failure behavior of railway assets. The findings of this study demonstrate the significant impact of climate change on railway infrastructure reliability, particularly in relation to changes in precipitation patterns. The results highlighted the importance of considering climate adaptation measures in the design and maintenance of railway systems, to ensure their continued safe and efficient operation in the face of different climate changing scenarios. It is recommended that future research in this area includes a broader range of covariates to gain a more comprehensive understanding of the relationship between climate change not only railway infrastructure reliability, but also other infrastructure behave differently but approach can be generic.

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