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TOPIC: ANALYISING LONG-TERM TRENDS IN BROKEN AND BUCKLED RAIL FAILURES IN THE UK MAINLINE RAIL NETWORK

SECTION 1

Introduction

1.1 Background and Context

The railway system is an essential element of the UK's transportation network. It enables the movement of both passengers and goods, significantly contributing to the economy (Office of Rail and Road, 2023). The infrastructure, composed of continuous welded rails, sleepers, and ballast, endures heavy loads, extreme weather conditions, and ongoing wear and tear (Esveld, 2001). Consequently, it is vital to maintain the tracks in optimal condition to ensure the safety and reliability of train operations (Kwaewunruen et al., 2018).

1.2 Literature Review

Two major types of track failures that raise safety concerns are broken rails and buckled rails. Broken rails, caused by fatigue or material defects, are a leading cause of derailments, making rapid detection and repair crucial (Cannon et al., 2003; Peng et al., 2011). Buckled rails occur due to thermal expansion that deforms the rail, particularly during high temperatures (Kerr, A.D., 2003; Zakeri & Xia, 2008). Both failure types compromise safety and lead to service disruptions (Network Rail, 2023).

While literature on rail mechanics and prevention exists (Esveld, C., 2001; Peng et al., 2011; Kaewunruen et al., 2018), there is a lack of long-term statistical analyses on broken and buckled rails in the UK. Most studies focus on laboratory tests or specific cases rather than broader trend analysis, which could inform strategic maintenance (Palin et al., 2013; Nezval et al., 2025).

This research utilizes annual national counts of broken and buckled rail incidents to provide a long-term view of infrastructure reliability and trends. Understanding changes in track failures over time is vital, especially as climate change impacts usage patterns, and this data-driven insight will guide inspection and investment strategies (Nezval et al., 2025; RSCB, 2021).

1.3 Research Aim

The aim of this study is to analyse long-term annual trends in broken rails and buckled rails in the UK rail network, and to assess how these two failure types have evolved over time using statistical exploratory analysis and appropriate trend models.

1.4 Research Questions

RQ1. What are the long-term trends in broken-rail and buckled-rail failures in the UK rail network?

RQ2. Does overdispersion affect statistical modelling of broken and buckled rail failures?

SECTION 2

METHODOLOGY

2.1 Dataset source

This quantitative study examines UK railway track failures, specifically broken and buckled rails, using 23 years of data (April 2002 to March 2025) from the Office of Rail and Road's annual reports. This long-term approach aims to identify reliability trends beyond short-term operational fluctuations.

2.2 Data Description

Variable	Description	Type
Year	Financial year observation	Time Index
Broken_Rails	Annual number of broken rail	Count
Buckled_Rails	Annual number of buckled rail	Count

2.3 Data Processing

In RStudio, the dataset was checked for missing, duplicate, or inconsistent values, and none were found. The financial year was converted to a numerical time index. The dataset was stored in both 'wide' and 'long' formats for easier visualization and modeling.

2.4 Exploratory Data Analysis

I started with Exploratory Data Analysis (EDA) to understand the structure and behavior of broken and buckled rail failures, which provided a solid foundation for further statistical modeling. EDA is crucial for identifying trends, outliers, and potential issues with modeling assumptions.

My EDA involved descriptive statistics, time-series plots, and analyzing data distributions, using specialized software ("moments") for skewed distributions. Time-series plots helped assess long-term trends and volatility, while histograms and variance comparisons aided in understanding the data distribution and checking for overdispersion, which is essential for selecting appropriate count-data models.

2.5 Statistical Modelling Strategy

Statistical modeling is crucial in railway engineering for assessing track degradation, defect progression, and failure risks. Andrews (2013) emphasizes probabilistic analysis for asset management, while Zhao et al. (2020) found that rail defect failure rates vary over time. Therefore, negative binomial regression is preferred over Poisson regression for modeling infrastructure reliability (Fox, 2016; Cameron & Trivedi, 2013; Lord & Mannering, 2010).

2.6 Model Justification

In railway engineering, statistical modeling serves as an essential tool for examining factors such as track degradation, the progression of defects, and the associated risks of failures. Andrews (2013) introduced a method for managing railway track assets through probabilistic analysis, highlighting the significance of statistical techniques in understanding the long-term reliability and degradation of infrastructure. Similarly, Zhao et al. (2020) employed statistical models to analyze rail defect data, revealing that failure processes exhibit considerable variability over time and do not maintain a constant variance. This finding underscores the necessity for flexible models when working with count data.

As a result, employing Poisson regression for basic comparisons and using negative binomial regression as our primary modeling approach aligns with established best practices for analyzing transportation safety and modeling infrastructure reliability (Fox, 2016; Cameron & Trivedi, 2013; Lord & Mannering, 2010).

2.7 Link between Methodology and Research Questions

Research question 1 is examined through exploratory data analysis, Poisson regression, and negative binomial regression. These methods collectively enable the study to identify, quantify, and statistically validate long-term trends related to failures.

Research question 2 is explored using overdispersion diagnostics and model comparison based on the Akaike Information Criterion.

SECTION 3

Results and Discussions

3.1 Exploratory Data Analysis

Broken rail counts ranged from 53 to 444, with a first quartile of 87, median of 120, and third quartile of 181.5, resulting in an IQR of 94.5. The mean count of 158.1 indicates a right-skewed distribution, primarily influenced by higher failure rates in the early 2000s.

For buckled rails, counts varied between 4 and 137, with a first quartile of 9, median of 14, and third quartile of 27, giving an IQR of 18. The mean count of 24.91 also shows a positive skew due to a few extreme events.

The variability in both broken and buckled rail counts points to inconsistent and non-stationary rail failures, attributed to factors like fatigue, track conditions, and environmental stresses. Aging infrastructure and inspection practices from the early 2000s likely contribute to broken rails, while buckling typically correlates with thermal stress events (Esveld, 2001; Cannon et al., 2003; Kaewunruen et al., 2018; Kerr, 2003; Talin et al., 2013).

3.1.1 Distributional Characteristics (Histogram Analysis)

A histogram of rail failures per year shows that both broken and buckled rails follow a "right-skewed" pattern.

Broken Rails: Most years report low broken rail incidents, but a few early years have spikes exceeding 400 failures, raising the average. Gaps in the distribution indicate no observations between 200–300 and 300–400 incidents, emphasizing the influence of these extreme values. (see fig 3.1.1a)

Buckled Rails: Similarly, buckled rails generally have fewer than 80 incidents yearly, with only a few years surpassing 100. This suggests that buckled rail failures occur in bursts, especially during extreme events. (see fig 3.1.1b)

The histograms confirm that rail failures aren't normal or predictable. They're skewed, with occasional extreme events that really stand out.

Fig 3.1.1a

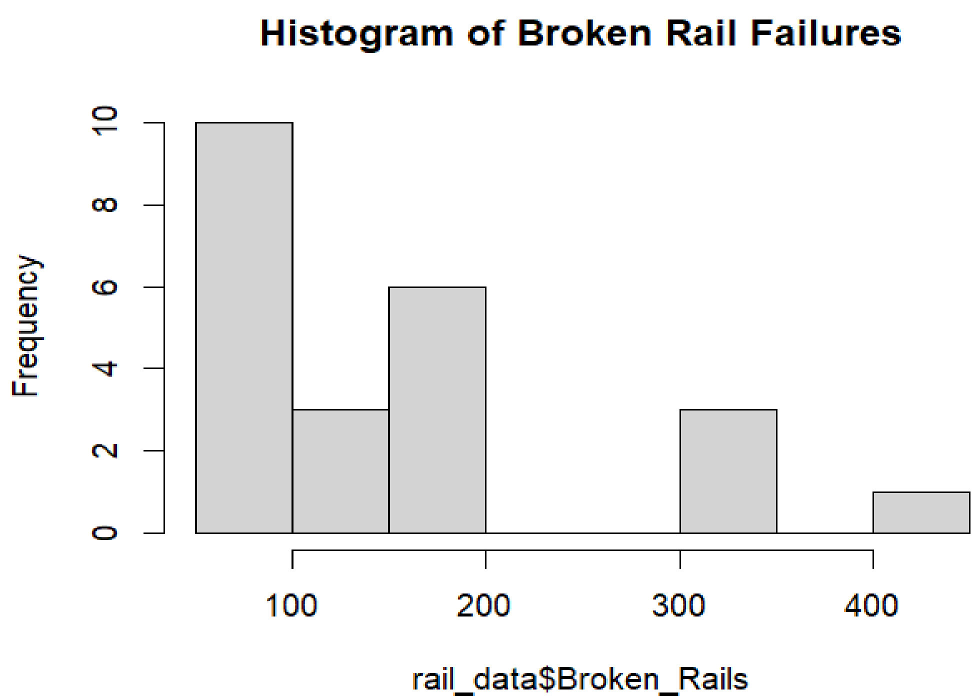
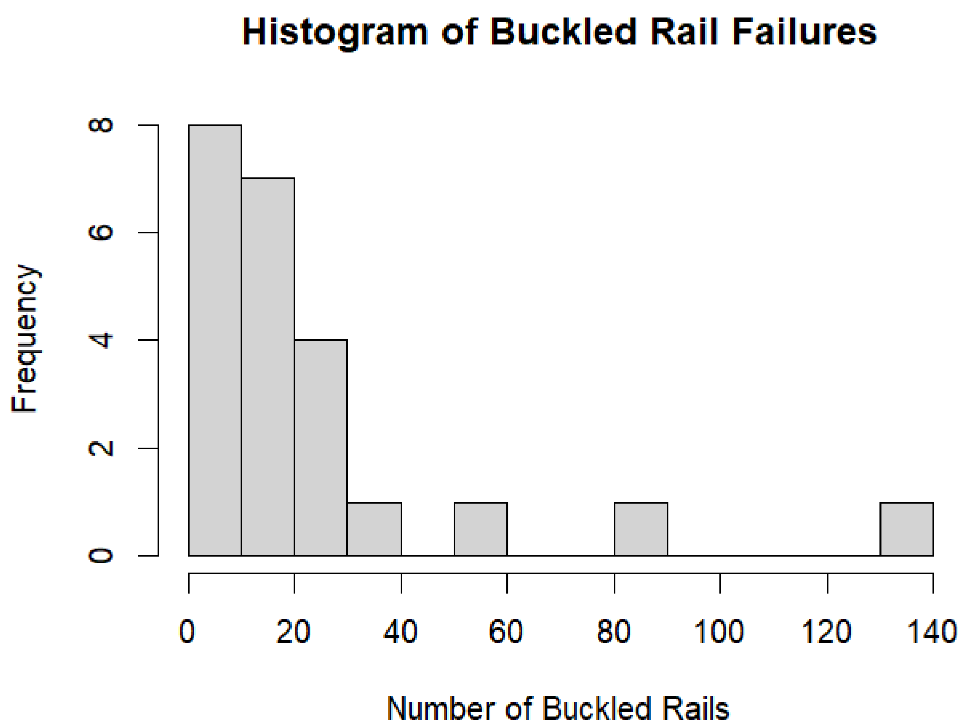

Histogram of Broken Rail Failures
Frequency
0
2
4
6
8
10
100
200
300
400
rail_data$Broken_Rails

Fig 3.1.1b

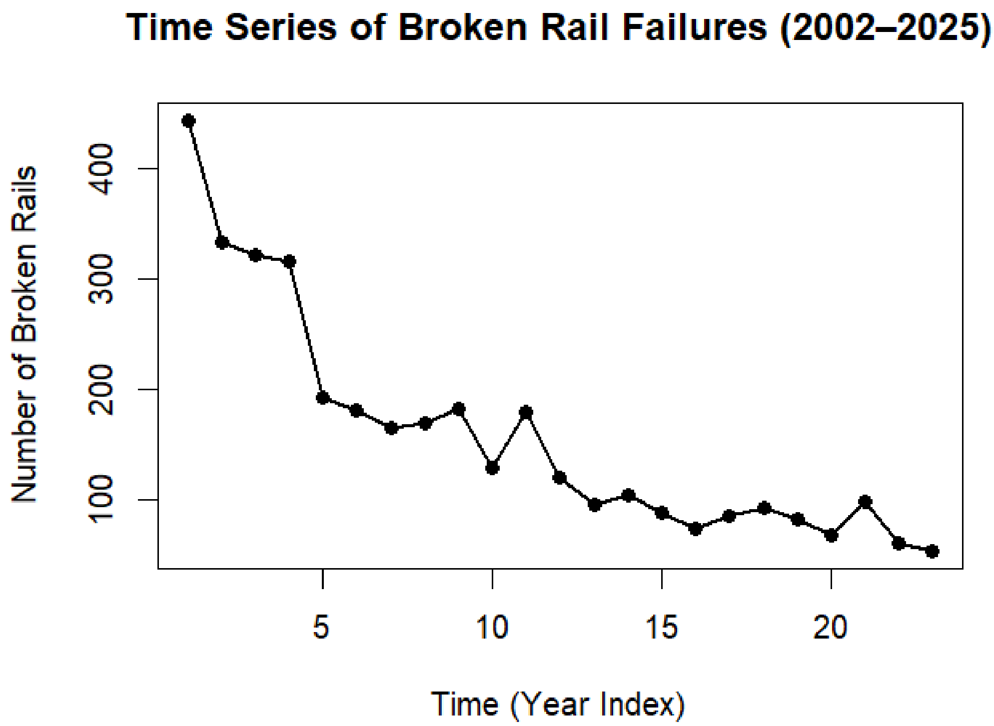


3.1.2 Time Series Trends

Time- series of broken Rails shows the number of broken rails has steadily decreased over the last 23 years, thanks to better infrastructure and inspection technology (Network Rail, 2023).

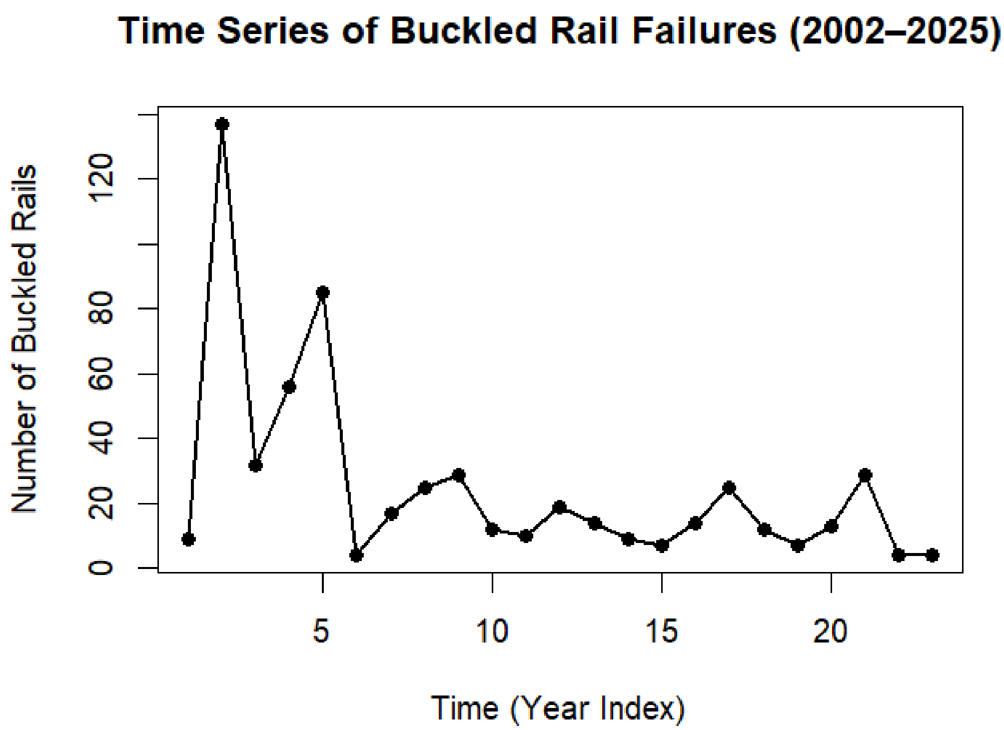
(see fig 3.1.2a)

Fig 3.1.2a

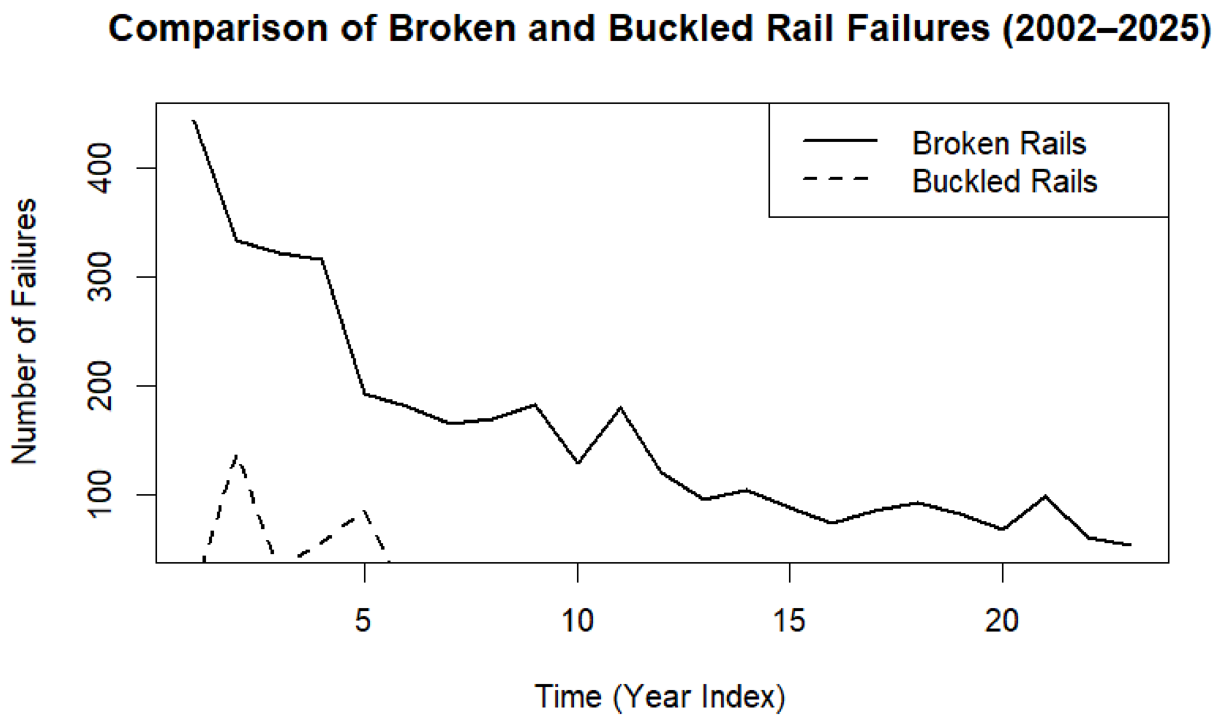


Buckled rail data is more erratic, with spikes in 2003-2004 and 2006-2007, primarily due to climate-related heat stress rather than maintenance improvements (Palin et al., 2013). Consequently, buckled rail failures do not consistently decrease like broken rails, despite ongoing maintenance. (see fig 3.1.2b)

Fig 3.1.2b



A comparative time series analysis indicates that broken and buckled rails exhibit distinct degradation dynamics. Broken rails primarily result from structural wear and tear, whereas buckled rails are more influenced by environmental factors. Consequently, it is essential to study these issues separately. (See diagram below)



3.2 Model Diagnostics (Overdispersion Diagnostics)

To assess the suitability of Poisson-based count models, dispersion ratios were calculated as the ratio of the sample variance to the sample mean for each failure series. The resulting dispersion statistics were:

Broken rails: dispersion ratio = 67.80

Buckled rails: dispersion ratio = 37.80

Interpretation Rule:

Dispersion Ratio	Meaning	Model Implication
=1	Poisson assumption valid	Poisson acceptable
>1.5	Moderate overdispersion	Negative Binomial required
<2	Strong overdispersion	Negative Binomial required

This means that dispersion ratios are much greater than 1, indicating severe overdispersion for both failure types. This violates the Poisson model's assumption that the mean and variance are equal, as the variance is 68 times larger than the mean for broken rails and 38 times larger for buckled rails (Cameron & Trivedi, 2013).

3.3 Poisson Regression (Baseline Model)

A Poisson regression model was used to analyze annual counts of broken rail failures, revealing a significant negative time trend ($\beta = -0.090$, $p < 0.001$), with an incidence rate ratio (IRR = 0.914) indicating an average annual decrease of about 8.6%. This decline is linked to infrastructure improvements by Network Rail. However, due to severe overdispersion, the Poisson model serves only as a baseline.

Similarly, the Poisson model for buckled rail failures shows a significant negative trend ($\beta = -0.100$, $p < 0.001$) and an IRR of 0.905, indicating an average 9.5% annual reduction, attributed to better management of thermal stresses. Again, the overdispersion issue requires the use of negative binomial regression for definitive conclusions.

3.4 Negative Binomial Regression

A negative binomial regression was conducted on broken rail counts to address overdispersion seen in the Poisson model. The time coefficient was negative and significant ($\beta = -0.0835$, $p < 0.001$), indicating an 8.0% average annual reduction in broken rail failures (IRR = 0.920). Model fit improved significantly, shown by an AIC drop from 279.82 to 219.49, making it the preferred approach, with a dispersion parameter of $\Theta = 36.53$ reflecting substantial unobserved heterogeneity.

Similarly, for buckled rail failures, a negative binomial regression was applied. The negative time coefficient ($\beta = -0.0876$, $p < 0.001$) indicated an 8.4% annual reduction in failures (IRR = 0.916). The model fit also improved, with an AIC of 187.50, establishing it as the preferred specification, and a dispersion parameter of $\Theta = 2.10$ indicating significant unobserved heterogeneity due to environmental factors.

3.5 Model Comparison Using Akaike Information Criterion (AIC)

Model performance, evaluated by the Akaike Information Criterion (AIC), showed that negative binomial models significantly outperformed Poisson models for both broken (AIC reduction >60) and buckled rails (AIC reduction >250). These substantial improvements highlight the Poisson models' inadequacy in handling overdispersion, while negative binomial models effectively accommodate unobserved heterogeneity. (see table below)

Model	AIC
Poisson – Broken rails	279.8174
Negative Binomial – Broken rails	219.4929
Poisson – Buckled rails	445.1211
Negative Binomial – Buckled rails	187.4978

3.6 Discussion

This study identifies a significant long-term decline in the incidence of broken and buckled rail failures in the UK, highlighting persistent improvements in track safety. Instances of broken rails were found to occur more frequently and exhibited greater variability, whereas buckled rails displayed fluctuating increases that corresponded with thermal stress events. These patterns align with existing research on rail safety.

The analysis confirms that rail failure data exhibit considerable overdispersion, making negative binomial regression a more suitable choice than Poisson models. This underscores the importance of selecting the appropriate model in safety analytics to prevent drawing misleading conclusions.

The findings provide strong evidence that sustained investment in inspection technology and track maintenance has resulted in lasting safety improvements. Key takeaways include the significance of long-term data for infrastructure monitoring, the necessity for robust statistical modeling, and the crucial role of data-driven analysis in informing rail safety decision-making.

3.6.1 Answers to research questions

RQ1: What are the long-term trends regarding broken-rail and buckled-rail failures in the UK rail network?

Answer: Both broken and buckled rail failures have experienced a significant decline over time, with an average reduction of approximately 8% per year. This trend reflects a sustained improvement in the reliability of the UK's track infrastructure.

RQ2: How does overdispersion impact the statistical modeling of broken and buckled rail failures?

Answer: Overdispersion has a substantial effect on the modeling process, indicating that Poisson regression is not appropriate. Consequently, it confirms that negative binomial regression is necessary for obtaining reliable results.

3.6.2 Relation to existing Research

This study confirms prior rail engineering and safety research. Consistent with (Network Rail, 2023; RSSB, 2022), our findings indicate that improved inspection, continuous welded rails, and thermal stress management reduce track failures. The observed downward trends align with UK rail infrastructure renewal efforts since the early 2000s, supported by investments in ultrasonic rail testing and heat monitoring (Network Rail, 2021). Furthermore, the statistical methods used, including the use of negative binomial models, are consistent with transportation safety research (Cameron & Trivedi, 2013), reinforcing both the engineering insights and the robustness of our study.

SECTION 4

R CODE AND GITHUB

4.1 R CODE

```
#Load data

g<- read.csv("C:/Rlab/Assesment intro data science/broken rails and buckled rails.csv")


rail_data<-data.frame(

  Year=c(

    "2002-2003","2003-2004","2004-2005","2005-2006","2006-2007",

    "2007-2008","2008-2009","2009-2010","2010-2011","2011-2012",

    "2012-2013","2013-2014","2014-2015","2015-2016","2016-2017",

    "2017-2018","2018-2019","2019-2020","2020-2021","2021-2022",

    "2022-2023","2023-2024","2024-2025"

  ),

  Broken_Rails=c(444,334,322,316,192,181,165,169,182,129,

               180,120,95,104,88,74,86,93,82,68,99,61,53

  ),

  Buckled_Rails = c(

    9,137,32,56,85,4,17,25,29,12,

    10,19,14,9,7,14,25,12,7,13,29,4,4

  )

)

View(rail_data)


summary(rail_data[,c("Broken_Rails","Buckled_Rails")])
```

```
#Exploratory Data Analysis

mean(rail_data$Broken_Rails)
mean(rail_data$Buckled_Rails)

var(rail_data$Broken_Rails)
var(rail_data$Buckled_Rails)

sd(rail_data$Broken_Rails)
sd(rail_data$Buckled_Rails)

range(rail_data$Broken_Rails)
range(rail_data$Buckled_Rails)

IQR(rail_data$Broken_Rails)
IQR(rail_data$Buckled_Rails)

install.packages("moments")
library(moments)

skewness(rail_data$Broken_Rails)
skewness(rail_data$Buckled_Rails)

descriptive_table <- data.frame(
  Variable = c("Broken Rails", "Buckled Rails"),
  Mean = c(mean(rail_data$Broken_Rails), mean(rail_data$Buckled_Rails)),
```

```
  Median = c(median(rail_data$Broken_Rails), median(rail_data$Buckled_Rails)),
  SD = c(sd(rail_data$Broken_Rails), sd(rail_data$Buckled_Rails)),
  Variance = c(var(rail_data$Broken_Rails), var(rail_data$Buckled_Rails)),
  Min = c(min(rail_data$Broken_Rails), min(rail_data$Buckled_Rails)),
  Max = c(max(rail_data$Broken_Rails), max(rail_data$Buckled_Rails)),
  IQR = c(IQR(rail_data$Broken_Rails), IQR(rail_data$Buckled_Rails))
)
descriptive_table
View(descriptive_table)

#plotting time series

rail_data$Time_Index<-1:nrow(rail_data)
plot(
  rail_data$Time_Index,
  rail_data$Broken_Rails,
  type = "l",
  lwd = 2,
  xlab = "Time (Year Index)",
  ylab = "Number of Broken Rails",
  main = "Time Series of Broken Rail Failures (2002–2025)"
)
points(
  rail_data$Time_Index,
  rail_data$Broken_Rails,
  pch = 16
```

```
)
plot(
  rail_data$Time_Index,
  rail_data$Buckled_Rails,
  type = "l",
  lwd = 2,
  xlab = "Time (Year Index)",
  ylab = "Number of Buckled Rails",
  main = "Time Series of Buckled Rail Failures (2002–2025)"
)
points(
  rail_data$Time_Index,
  rail_data$Buckled_Rails,
  pch = 16
)

plot(
  rail_data$Time_Index,
  rail_data$Broken_Rails,
  type = "l",
  lwd = 2,
  xlab = "Time (Year Index)",
  ylab = "Number of Failures",
  main = "Comparison of Broken and Buckled Rail Failures (2002–2025)"
)
lines(
```

```
  rail_data$Time_Index,
  rail_data$Buckled_Rails,
  lwd = 2,
  lty = 2
)
legend(
  "topright",
  legend = c("Broken Rails", "Buckled Rails"),
  lty = c(1, 2),
  lwd = 2
)

# Plotting a histogram
hist(
  rail_data$Broken_Rails,
  main ="Histogram of Broken Rail Failures",
  x1ab ="Number of Broken Rails",
  breaks = 10
)
hist(
  rail_data$Buckled_Rails,
  main = "Histogram of Buckled Rail Failures",
  xlab = "Number of Buckled Rails",
  breaks = 10
)
```

```r
mean_broken <- mean(rail_data$Broken_Rails)
var_broken <- var(rail_data$Broken_Rails)

mean_broken
var_broken

mean_buckle <-mean(rail_data$Buckled_Rails)
var_buckle <-var(rail_data$Buckled_Rails)

mean_buckle
var_buckle

#Model diagnostics (overdispension)

dispersion_broken <- var_broken / mean_broken
dispersion_broken

dispersion_buckle <-var_buckle / mean_buckle
dispersion_buckle

#Poisson Regression

pois_broken <- glm(
  Broken_Rails ~ Time_Index,
  family = poisson,
  data = rail_data
```

```
)
summary(pois_broken)
exp(coef(pois_broken))

pois_buckle <- glm(
  Buckled_Rails ~ Time_Index,
  family = poisson,
  data = rail_data
)
summary(pois_buckle)
exp(coef(pois_buckle))

AIC_pois_broken <- AIC(pois_broken)
AIC_pois_buckle <- AIC(pois_buckle)
AIC_pois_broken
AIC_pois_buckle

install.packages("MASS")
library(MASS)

# Negative binomial regression

nb_broken <-glm.nb(
  Broken_Rails ~ Time_Index,
  data = rail_data
)
```

```r
summary(nb_broken)
exp(coef(nb_broken))
AIC_nb_broken <- AIC(nb_broken)
AIC_nb_broken

nb_buckle <- glm.nb(
  Buckled_Rails ~ Time_Index,
  data = rail_data
)
summary(nb_buckle)
exp(coef(nb_buckle))
AIC_nb_buckle <- AIC(nb_buckle)
AIC_nb_buckle

# Model comparison

model_comparison <- data.frame(
  Model = c(
    "Poisson - Broken Rails",
    "Negative Binomial - Broken Rails",
    "Poisson - Buckled Rails",
    "Negative Binomial - Buckled Rails"
  ),
  AIC = c(
    AIC_pois_broken,
    AIC_nb_broken,
```

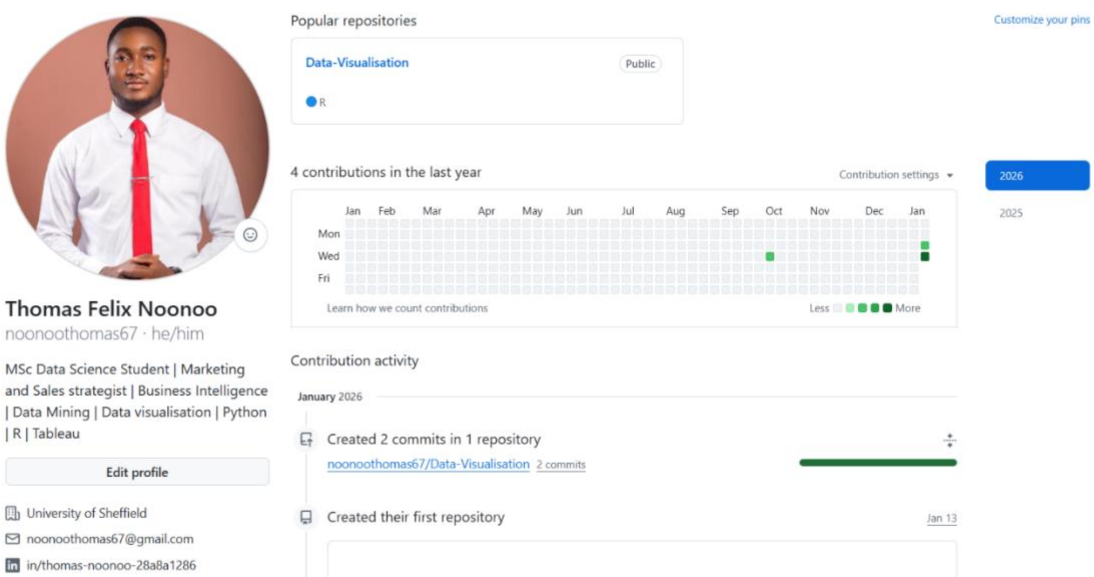
```
    AIC_pois_buckle,
    AIC_nb_buckle
  )
)

model_comparison
View(model_comparison)
```

4.2 GITHUB

GITHUB PROFILE

https://github.com/noonoothomas67

The profile README provides an overview of my academic background, technical skills, and featured data science projects. It highlights my interests in data analysis, visualisation, and statistical modelling, with direct links to my coursework projects.



Project

The IJC437 project repository is available at:

https://github.com/noonoothomas67/Intro-to-Data-Science

this repository includes:

- The Analysis script
- Generated plot images
- The Analysis report
- Dataset
- A README describing the overview, research questions, methods, key findings, tools used.

noonoothomas67 Update README.txt bcb5a27 · now **2 Commits**

Plots	first submit	8 minutes ago
DS report.pdf	first submit	8 minutes ago
Intro to data science coursework.R	first submit	8 minutes ago
README.txt	Update README.txt	now
broken rails and buckled rails.csv	first submit	8 minutes ago

README

```
UK Rail Track Failure Analysis (2002-2025)

Project Overview
This project analyses long-term trends in broken and buckled rail failures on the UK mainline railway network using annual
data from 2002 to 2025. The aim is to explore how rail infrastructure safety has changed over time and to identify suitable
statistical models for analysing overdispersed failure count data.
The project applies exploratory data analysis, visualisation, and count-data regression models to support evidence-based
insights into rail safety performance.

Research Questions
-What are the long-term trends regarding broken-rail and buckled-rail failures in the UK rail network?
-How does overdispersion impact the statistical modeling of broken and buckled rail failures?
```

Code

All code used in project is stored in clearly labelled Intro to data science coursework.R

GitHub allows the code to be viewed directly in the browser, making it easy for users to review the methods and reproduce the analysis.

Intro to data science coursework.R	first submit	14 minutes ago

Instructions on Running the Code

Each repository includes a How to Run section in the README file. These instructions explain:

1. How to download or clone the repository
2. How to open the R script in RStudio
3. How to load the dataset
4. How to run the code to reproduce the analysis and visualisations

```
How to Run the Code
1.Download or clone this repository
2.Open the file Intro to data science coursework.R in RStudio
3.Ensure the dataset broken rails and buckled rails.csv is in the same folder as the script
4.Install required packages if needed
5.Run the script to reproduce the analysis and results

Required packages:
-ggplot2
-MASS
```

SECTION 5

CONCLUSION

This study examined long-term trends in broken and buckled rail failures across the UK rail network using data from 2002 to 2025. The analysis revealed substantial declines in both failure types, supported by statistical modeling that indicated these reductions were significant. Due to overdispersion in the data, negative binomial regression was chosen, providing a better fit than Poisson models. The results align with existing literature, highlighting that sustained investments in track renewal and inspection technologies contribute to long-term safety improvements. This underscores the importance of combining exploratory visualization with robust statistical modeling for evidence-based decision-making in rail infrastructure management.

5.1 REFLECTION

5.1.1 Key Findings

- Rail failures (broken and buckled) have significantly declined.
- Broken rails were historically more frequent and variable.
- Data overdispersion favors negative binomial models.
- Findings support proactive rail maintenance effectiveness.

5.1.2 Limitations, Assumptions, and Weaknesses

Limitations:

- Small sample size limits statistical power.
- Annual data masks short-term and seasonal effects.
- Limited variables restrict causal mechanism identification.

Assumptions:

- Consistent reporting over time.
- Independence of annual counts.

Weaknesses:

- Aggregated annual data.
- Lack of explanatory variables.
- No spatial breakdown.

5.1.3 Future Work

- Link failures to operational outcomes (delays).
- Add spatial analysis to identify geographic variation.
- Incorporate higher-frequency data to capture short-term dynamics.

This study shows how combining exploratory analysis, visualization, and count-data modeling can analyze rail safety trends. The findings emphasize model selection for overdispersed data and data-driven analysis for rail safety management decisions.

5.2 Engagement

As a person new to the world of data, the employability sessions, alumini events and industrial events gave me understanding the demands of the corporate field. I got to understand that the field is a great opportunity to put into practice what was taught in school. The application of the data cycle doesn’t change and one must enjoy that their data is able to tell an insightful story that will change decisions or make decisions. I also got to know that I must look to learn more skills that are not being taught in the classroom to ensure I am prepared for any task that comes my way. This has been at the back of my mind as I am currently engaged in various volunteering data science activities to improve my skills.

REFERENCES

Andrews, J. D. (2013). A modelling framework for railway track asset management. *Reliability Engineering & System Safety, 120*, 76–93.

Cameron, A. C., & Trivedi, P. K. (2013). *Regression analysis of count data* (2nd ed.). Cambridge University Press.

Cannon, D. F., et al. (2003). Rail defects: An overview. *Fatigue & Fracture of Engineering Materials & Structures, 26*(10), 865–886.

Esveld, C. (2001). *Modern railway track* (2nd ed.). MRT-Productions.

Fox, J. (2016). *Applied regression analysis and generalized linear models* (3rd ed.). SAGE Publications.

Kaewunruen, S., Remennikov, A. M., & Baniotopoulos, C. (2021). Influences of ballast degradation on railway track buckling. *Construction and Building Materials, 187*, 1176–1184.

Kerr, A. D. (2003). On the buckling of railway tracks. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 217*(4), 207–221.

Lord, D., & Mannering, F. (2010). The statistical analysis of crash-frequency data: A review and assessment of methodological alternatives. *Transportation Research Part A: Policy and Practice, 44*(5), 291–305.

Nezval, V., Andrášik, R., & Bíl, M. (2025). Identification of factors contributing to broken and buckled rails: insights from long-term data. *European Transport Research Review, 17*(28).

Network Rail. (2023). *Broken rail: What it means and how it affects the railway*.

Office of Rail and Road. (2023). *Rail safety statistics 2022–2023*.

Palin, E. J., et al. (2013). Climate change impacts on rail infrastructure in the UK. *Proceedings of the ICE – Engineering Sustainability, 166*(5), 247–257.

Peng, J., et al. (2011). Analysis of rail crack propagation under rolling contact fatigue. *Engineering Fracture Mechanics, 78*(14), 2637–2649.

Rail Safety and Standards Board. (2021). *Guidance on management of track buckling risk*.

Tukey, J. W. (1977). *Exploratory data analysis*. Addison-Wesley.

Zakeri, J. A., & Xia, H. (2008). Sensitivity analysis of track buckling in continuous welded rail. *Engineering Structures, 30*(12), 3419–3427.

Zhao, X., Chen, H., & Roberts, C. (2020). Analysis of rail defect growth and failure risk using statistical degradation models. *Engineering Failure Analysis, 115*, 104640.