Understanding Incident Trends: A Deep Dive Into Train Incidents

B.B.S Makhanya[1*] & J.H.C. Pretorius[1]

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Contact details
* Corresponding author
bmakhanya@uj.ac.za

Author affiliations
1 Postgraduate School of Engineering Management, University of Johannesburg, South Africa

ORCID® identifiers
B.B.S Makhanya
https://orcid.org/0000-0002-6185-2333

J.H.C. Pretorius
https://orcid.org/0000-0002-2023-749X

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ABSTRACT

This study investigates the factors leading to the classification of locomotives as long-standing (out of service for over 50 days) in South Africa. It focuses on trends in train incidents, identifying 363 long-standing locomotives with unscheduled maintenance, collisions, and vandalism listed as the primary incident types. Time series decomposition uncovered a seasonal pattern, and correlation analysis showed significant relationships among these incident categories. The Prophet model was selected for forecasting, predicting an increase in incidents related to maintenance, collisions, and vandalism. The study emphasises the need for further research on the impact of incidents on safety, operations, and personnel, as well as the effectiveness of safety training programmes. The findings stress the importance of understanding incident trends and their implications for railway safety and operational efficiency, providing insights for strategies to mitigate the impact of train incidents in South Africa.

OPSOMMING

Hierdie studie ondersoek die faktore wat lei tot die klassifikasie van lokomotiewe as lank-onaktief (buite diens vir meer as 50 dae) in Suid-Afrika. Dit fokus op tendense in treinvoorvalle en identifiseer 363 lank-onaktiewe lokomotiewe met ongeskeduleerde instandhouding, botsings en vandalisme wat as die primêre voorvaltipes gelys word. Tydreeksontbinding het 'n seisoenale patroon onthul, en korrelasie-analise het beduidende verwantskappe tussen hierdie voorvalkategorieë getoon. Die Prophet-model is gekies vir voorspelling, wat 'n toename in voorvalle wat verband hou met instandhouding, botsings en vandalisme voorspel. Die studie beklemtoon die behoefte aan verdere navorsing oor die impak van voorvalle op veiligheid, bedrywighede en personeel, sowel as die doeltreffendheid van veiligheidsopleidingsprogramme. Die bevindinge beklemtoon die belangrikheid daarvan om voorvaltendense en hul implikasies vir spoorwegveiligheid en operasionele doeltreffendheid te verstaan, en bied insigte vir strategieë om die impak van treinvoorvalle in Suid-Afrika te verminder.

1. INTRODUCTION

The trends in rolling stock incidents, including accidents involving trains and other rail vehicles, have significant implications for human life and the economy [1], [2]. Recent studies indicate that railway incidents can have severe consequences, including fatalities and injuries among passengers and railway personnel [3], [4]. For instance, Hall *et al.* [1] conducted a detailed analysis of 263 pedestrian incidents in New York City's subway system, and found that elevated stations had a higher fatality rate (40%) than below-ground stations (27%). This highlights the urgent need for improved safety measures and infrastructure enhancements to mitigate the risks associated with train operations. The economic implications of rolling stock incidents are substantial. Accidents can result in significant financial losses from equipment damage, service disruptions, and legal liabilities. For example, the correlation between occupational accidents and economic factors has been studied in China, revealing that increased investment in safety training and infrastructure could reduce accidents and the associated costs [2]. The economic impact of railway incidents goes beyond immediate financial losses; it also includes long-term effects on community trust in rail services and the potential decline in ridership, which could strain financial resources further. The economic implications of such incidents are complex, comprising direct costs such as damage to infrastructure and rolling stock alongside indirect expenses such as lost productivity, legal liabilities, and enduring impacts on public confidence in rail services [5], [6]. Bridgelall and Tolliver [5] highlighted that derailments account for up to 70% of the total costs associated with incidents in the United States annually. Kim *et al.* [6] studied 15 years' (2008 to 2022) worth of incident data in Korea and found that the incident cost was a function of season, train type, facility involved, location, and person involved. Understanding these economic implications would be essential for developing effective safety strategies and improving the overall efficiency of railway operations.

The psychological impact of incidents on train drivers is significant, with research indicating that such events can result in long-term psychological effects. This underscores the need for effective incident management and support protocols [4]. The psychological repercussions extend beyond those directly involved, resulting in broader operational inefficiencies that have an impact on service reliability and the public's perception of rail safety. This underscores the importance of studies such as the current research, which aims to enhance our understanding of trends and provide further predictions to help to develop effective strategies to mitigate the impact of incidents.

Hugelius *et al.* [3] maintained that implementing comprehensive training programmes for railway personnel would have enhanced safety outcomes. Training programmes emphasising emergency preparedness and incident management could considerably reduce the likelihood of accidents and improve response times during crises. This would be essential to safeguard the well-being of passengers and staff and to ensure the economic viability of rail operations. Moreover, practical training fosters better decision-making under pressure – a critical skill in the high-stakes situations frequently encountered in the rail industry [7]. Investing in extensive training, innovative research, and cutting-edge technology represents a crucial strategy for effectively addressing train incidents. This foundational work sets the stage for this study, which aims to respond to the following research question.

1.1. Research questions

A) What are the primary factors leading to locomotives being classified as long-standing (out of service for more than 50 days) in South Africa?

B) What are the trends in train incidents, and which incident categories have significantly influenced the overall number of long-standing assets?

C) Can we mathematically explain the trends in incident categories, based on the occurrence of other categories, specifically the incident, which significantly affect the overall number of long-standing assets?

2. RELATED WORK

Tang *et al.* [8] reviewed train post-derailment behaviours and containment methods, emphasising the critical need for effective strategies to mitigate the severe consequences of derailments, which account for over 60% of serious railway accidents. They analysed case studies from different regions, including the United States (citing The Federal Railroad Administration (FRA) statistics), Europe (referencing European Union Agency data), Japan (discussing post-2004 Niigata Chuetsu earthquake developments), and South

Korea (examining their guard rail system). In a separate study, Bridgelall and Tolliver [5] suggested that derailment numbers could go up to 70% in the United States. Tang *et al.* [8] systematically explored the factors influencing post-derailment dynamics, including derailment speed, train weight, and track conditions, while introducing substitute guidance mechanisms as passive safety measures. They identified several key research gaps in the existing body of knowledge and challenges, including:

- Modelling and simulating derailments: The complex behaviour following a derailment presents a significant problem for modelling owing to highly nonlinear interactions.
- Standardisation issues: A notable lack of unified standards for post-derailment containment leads to most practical applications being handled on a case-by-case basis. Consequently, there is no standard reference approach to studying post-derailment containment.
- Safety infrastructure: There is an urgent need for more efficient and cost-effective facilities for passive safety protection. The effectiveness of current protective measures has not been thoroughly investigated. This highlights the pressing need for improved containment methods, addresses unresolved problems, and underscores the need for standardised practices. The discussion also includes dynamic modelling and simulation techniques that help to understand train behaviour after a derailment, ultimately providing valuable insights for railway industry professionals to enhance safety and minimise catastrophic outcomes.

Al-Masaeid and Khaled [9] conducted a study of traffic accidents in Jordan from 1995 to 2020, using regression analysis, artificial neural networks (ANN), and autoregressive integrated moving average (ARIMA) models. Their research aimed to assess the impact of COVID-19 travel restrictions on traffic accident data. The results revealed an increasing trend in accidents, fatalities, and injuries, with ANN models demonstrating superior predictive accuracy than regression and ARIMA models. Notably, government measures during the pandemic significantly reduced accidents and casualties, underscoring the effectiveness of policy interventions on safety. In addition, the study emphasised the importance of incorporating factors such as population, registered vehicles, and gross domestic product into accident prediction modelling, providing a comprehensive framework for understanding traffic incidents.Similarly, Ragala, Retbi and Bennani [10] focused on machine learning applications in analysing daily failure data, using models such as long short-term memory (LSTM), bidirectional LSTM (BiLSTM), gated recurrent unit (GRU), and support vector regression (SVR). Their findings highlighted a root mean square error (RMSE) as low as 0.006 with the LSTM model, and achieved a classification accuracy of 61.73% using ensemble learning techniques. Their research stressed the significance of predictive analytics for timely maintenance and improved system reliability, using data from the open datasets of SNCF (the French national railway company).

Chen *et al.* [11] reviewed methodologies for predicting delays in urban railway systems, categorising them into statistical methods and machine learning techniques. Their analysis of a large dataset from Hong Kong revealed that statistical models generally outperformed machine learning models in predicting delays, with quantile regression, support vector regression, and XGBoost performing exceptionally well. The study identified the key factors influencing delays, highlighting the need for effective management strategies to address disruptions.

Zhao *et al.* [12] introduced eWarn, a real-time incident prediction approach to improve service quality and minimise economic losses. This method uses historical alert data and employs advanced feature engineering, multi-instance learning, and the XGBoost classification model for predictions. eWarn provides interpretable reports through Local Interpretable Model-agnostic Explanations (LIME), aiding engineers in understanding predictive outcomes. Evaluations across 11 real-world systems in a significant commercial business showcased eWarn's outstanding performance and significantly outperformed existing methods, illustrating its practical utility in real-world applications.

In summary, Tang *et al.* [8] emphasised the significance of effective post-derailment strategies and identified research gaps related to modelling and standardisation. Al-Masaeid and Khaled [9] used regression analysis and machine learning to examine traffic accidents in Jordan, demonstrating the impact of policy decisions. Ragala, Retbi and Bennani [10] focused on using predictive analytics for maintenance by applying machine learning techniques to daily failure data. Chen, Ma and Sun [11] found that statistical models outperformed machine learning in forecasting urban railway delays. In addition, Zhao *et al.* [12] introduced eWarn, a real-time incident prediction method that leverages historical data, highlighting the critical role of predictive analytics in maintenance and reliability. Overall, these studies underscore the need to understand the dynamics associated with train incidents, the ability to categorise such incidents, and the application of predictive analytics and modern technology for timely alerts.

3. METHODS

In this study, the research team was granted a period of three weeks to evaluate the condition of long-standing locomotives. For the purpose of this case study, the term "long-standing asset" refers to any locomotive that has been out of service for more than 50 days. Several factors, including incidents, in-line failures, theft, and vandalism, can render an asset unavailable.

The data collection process involved visits to depots throughout South Africa, where we identified long-standing assets. We created a template that included the asset number, manufacturer, reasons for removal from service, and explanations for not repairing and returning the asset to operation. Depot managers and asset owners assisted us in inspecting the locomotives and evaluating their impact on overall business performance. Their involvement was crucial, as they had firsthand knowledge of the assets and were engaged in maintenance planning and execution.

To analyse the data for this research, we used Python 3.12.3 and its associated packages. Python was selected for its scalability and ease of implementation, especially in industrial settings where domain experts may lack formal training in data science. The comprehensive ecosystem of libraries, such as pandas for data manipulation, matplotlib for data visualisation, and fbprophet for time series forecasting, facilitated efficient analysis and model deployment. Consequently, Python emerged as an ideal choice to address the complexities of incident trend data in railway operations.

3.1. Data collection

The research identified a total of 363 long-standing locomotives. The majority, 152, were stationary because of unscheduled maintenance issues, with the lack of available spares cited as the primary reason for the repair delays (Figure 1). The data revealed that unscheduled maintenance, collisions, and vandalism were the three most frequent incident types affecting these assets.

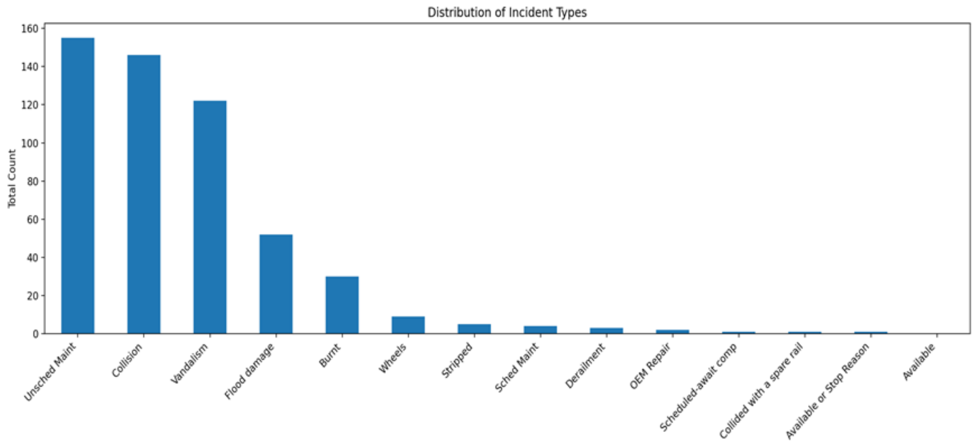

Figure 1: Distribution of incident types

3.2. Data processing

Scheduled maintenance, collisions, and vandalism were identified as the main reasons for classifying an asset as a long-standing asset. Therefore, these three categories were chosen for a more thorough analysis. Figure 2 illustrates the annual trends for these incidents, all showing an upward trajectory, driven primarily by unscheduled maintenance activities. The historical data began in 2001, but the variability in the dataset became most evident from 2016 onwards.

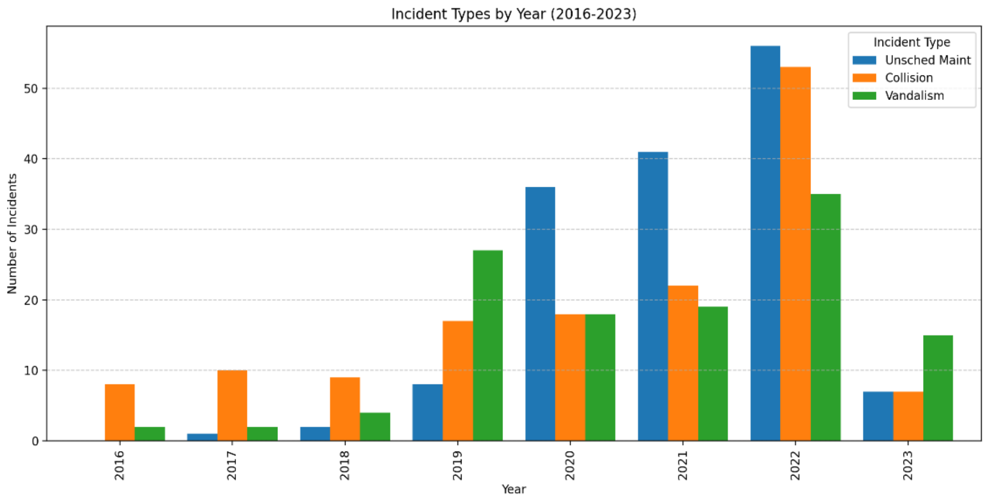

Figure 2: Incident types by year (2016–2024)

As part of the data analysis, we also had to do time series decomposition to check for the seasonal patterns for "unscheduled maintenance", "collisions", and "vandalism" (Figure 3).

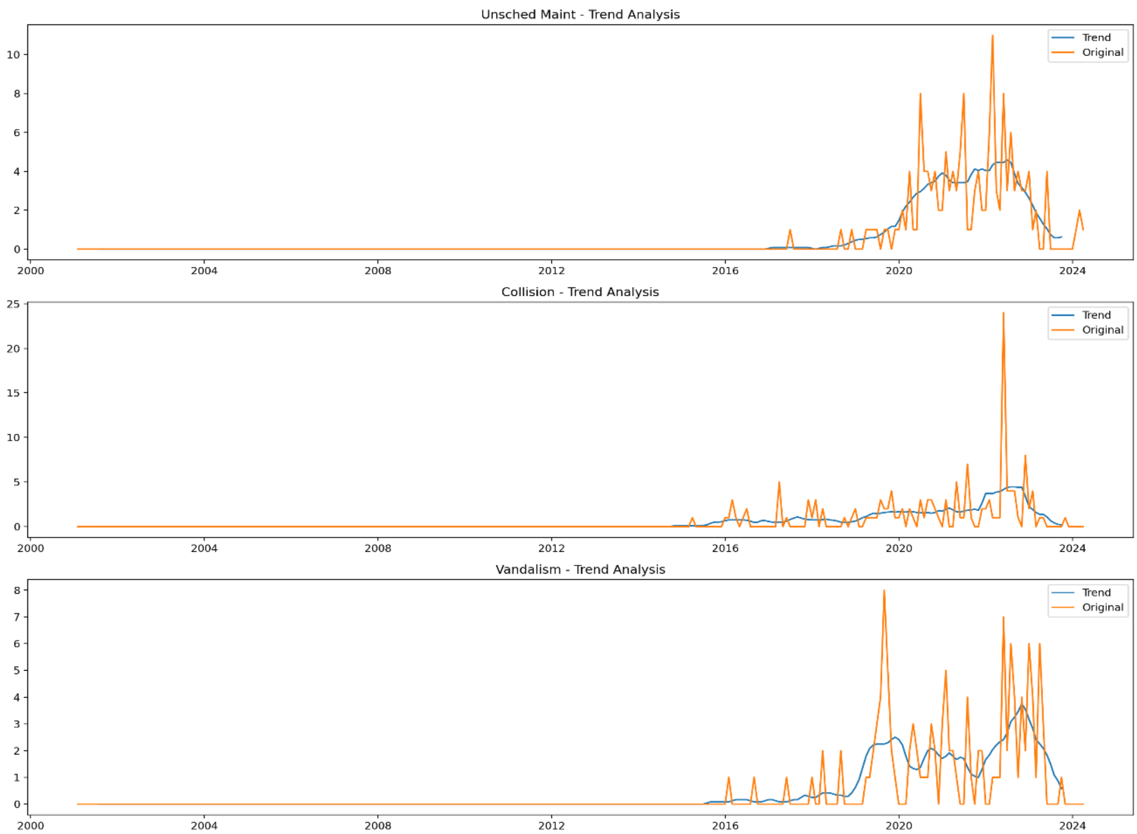

Figure 3:Time series decomposition (trend analysis)

The data indicates some seasonality in the occurrence of the observed incidents, with a peak in vandalism incidents in 2019. More collisions were reported in 2022, and an increased seasonality was observed in unscheduled maintenance activities.

3.3. Correlation analysis

To explore the potential relationships between the categories of “unscheduled maintenance”, “collisions”, and “vandalism”, we analysed them by calculating the correlation coefficients for these variables. Our objective was to quantify both the strength and direction of their relationships. To enhance our understanding, we created a pair plot to represent these correlations (Figure 4). This graphical tool enabled us to observe any linear relationships or patterns among the variables, providing valuable insights into how they might influence one another. The statistical tests confirmed the relationships between the variables, with significant p-values indicating that the correlations were unlikely to be the result of random chance.

For instance, the correlation between unscheduled maintenance and collisions is r = 0.352 with a p-value of 0.00078, indicating a moderate positive correlation that is statistically significant. The relationship between unscheduled maintenance and vandalism shows a correlation coefficient of 0.269 and a p-value of 0.011, representing a weak positive correlation that is also statistically significant. In contrast, the correlation between collisions and vandalism has a coefficient of 0.455 and a p-value of 8.617e-06, indicating a moderate positive correlation that is highly significant. This analysis suggests that, while all three variables are somewhat interrelated, the strongest relationship is between collisions and vandalism.

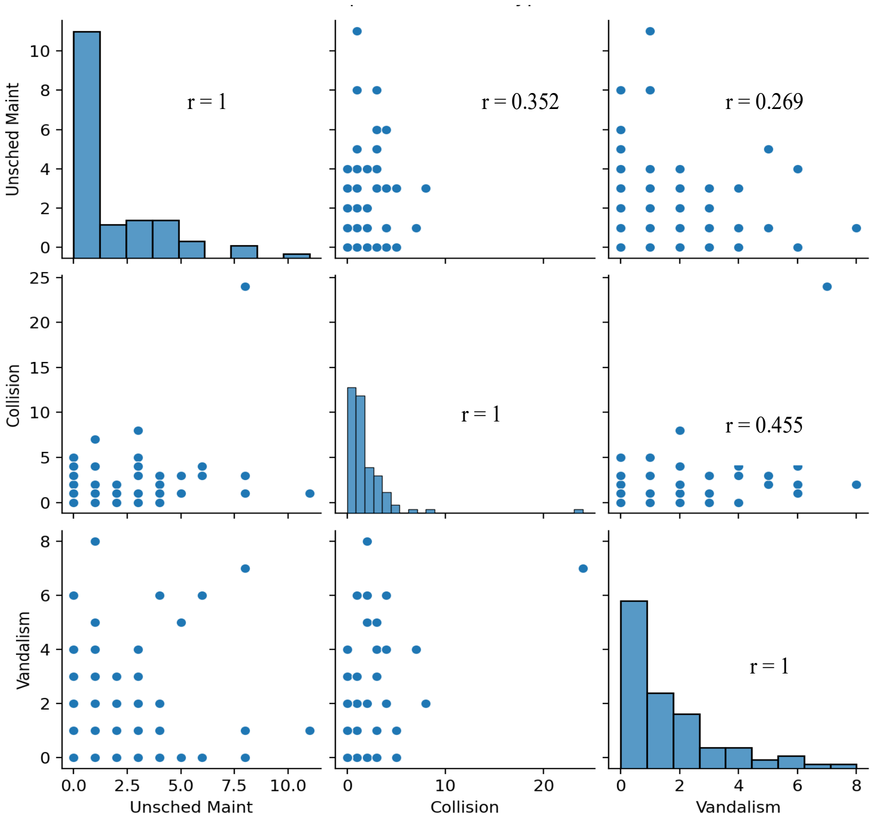

Figure 4: Correlation analysis

3.4. Model selection

This research aimed to re-evaluate the prevalence of long-standing locomotives by using insights from a previously published paper [13]. The earlier study noted observable trends, but did not forecast how each category might change in the near future. In this study, we concentrated on forecasting the three categories and elucidating how they would likely evolve, based on these observed patterns. To ascertain which model best fitted the data, we compared two time series models, ARIMA (1,1,1) [14], [15] and Prophet. ARIMA is a statistical modelling approach that combines three key components: the “autoregressive” (AR) component, the “moving average” (MA) component, and the “integrated” (I) component. The model is represented as ARIMA (p, d, q):

- AR(p) model: This component defines the relationship between current values and their past values.
- MA(q) model: This component illustrates the relationship between current values and past errors.
- Integrated (I) component: This adjusts the time series data to make it stationary.

The ARIMA modelling process involves four main steps: identification, estimation, diagnostic testing, and forecasting. ARIMA has been widely used in transportation planning, particularly to predict traffic flow, travel time, and freight volumes.

Prophet is a forecasting model developed by Facebook (now Meta) in 2017 by Taylor and Letham [17]. It is designed to be a comprehensive, user-friendly forecasting tool with several key features. The model allows users to generate individual forecast components, including trend, seasonality (both yearly and weekly), and holiday effects, using the Fourier series for seasonal modelling. It is particularly notable for its ease of interpretation, making it accessible to managers without expert statistical knowledge.

In this study, the ARIMA model yielded negative R-squared scores for all three variables, indicating its unsuitability for forecasting these occurrences (Table 1). This disappointing performance suggested that ARIMA may not have been an appropriate choice for this data, likely because of issues related to non-stationarity or complex seasonal patterns. As an alternative, we investigated the Prophet model, which accommodates seasonality and trends more effectively. The Prophet model produced positive R-squared values, explaining 41.56% of the variance in the unscheduled maintenance variable based on time variables, 18.81% variance in collisions, and 31.71% in vandalism. Thus we selected the Prophet model as the focus model for this paper.

Table 1: Model accuracy

Model	**ARIMA (1,1,1)**			**Prophet**		
Statistics	Unscheduled maintenance	Collision	Vandalism	Unscheduled maintenance	Collision	Vandalism
Mean squared error	4.1814	7.7278	9.6688	1.3090	2.6061	1.0101
Mean absolute error	1.9479	2.7558	3.0374	0.5901	0.6696	0.5479
R-squared score	-2.0106	-54.6398	-12.3875	0.4156	0.1881	0.3171

4. RESULTS

Figure 5 illustrates the forecast results derived from the Facebook Prophet model. The blue line represents the anticipated unscheduled maintenance for long-standing assets, showing a clear trend over time. Accompanying this forecast, the shaded area around the blue line indicates the confidence interval, reflecting the level of uncertainty associated with the projections. This visual representation allows for a more nuanced understanding of potential fluctuations in maintenance needs.

From 2000 to 2016, there was a consistent increase in unscheduled maintenance events, followed by a decline and a sharp rise. After 2020, the forecast displayed significant fluctuations with greater uncertainty, as indicated by the wider shaded region. Unscheduled maintenance was projected to average six locomotives and to increase to an average of eight locomotives by 2026 per year.

The yellow line in the collision forecast graph illustrates the number of collisions over time, while the shaded areas denote uncertainty. The data remained stable from 2000 to 2016; it experienced a marked increase in 2016, followed by elevated activation rates. Although collisions remained relatively stable, fluctuations were still observed. The forecast exhibited a moderate upward trend, with values ranging from 0 to 10 units.

The graph also features a green line representing the forecast values for vandalism over time. From 2000 until around 2016, the forecast indicated a steady upward trend. A sharp increase occurred around 2016, followed by ongoing fluctuations. After 2020, the forecast showed some stabilisation, although fluctuations persisted with values ranging from around two to 10 units.

All three forecasts show significant changes from 2016, suggesting a potential event or shift in data trends. The uncertainty, represented by the shaded regions, increases over time in all graphs, reflecting decreased confidence in forecasts for later years. Notably, the fluctuations in estimates become more pronounced after 2020, particularly for unscheduled maintenance and collisions. Significant shifts in patterns are evident around 2016 in all metrics.

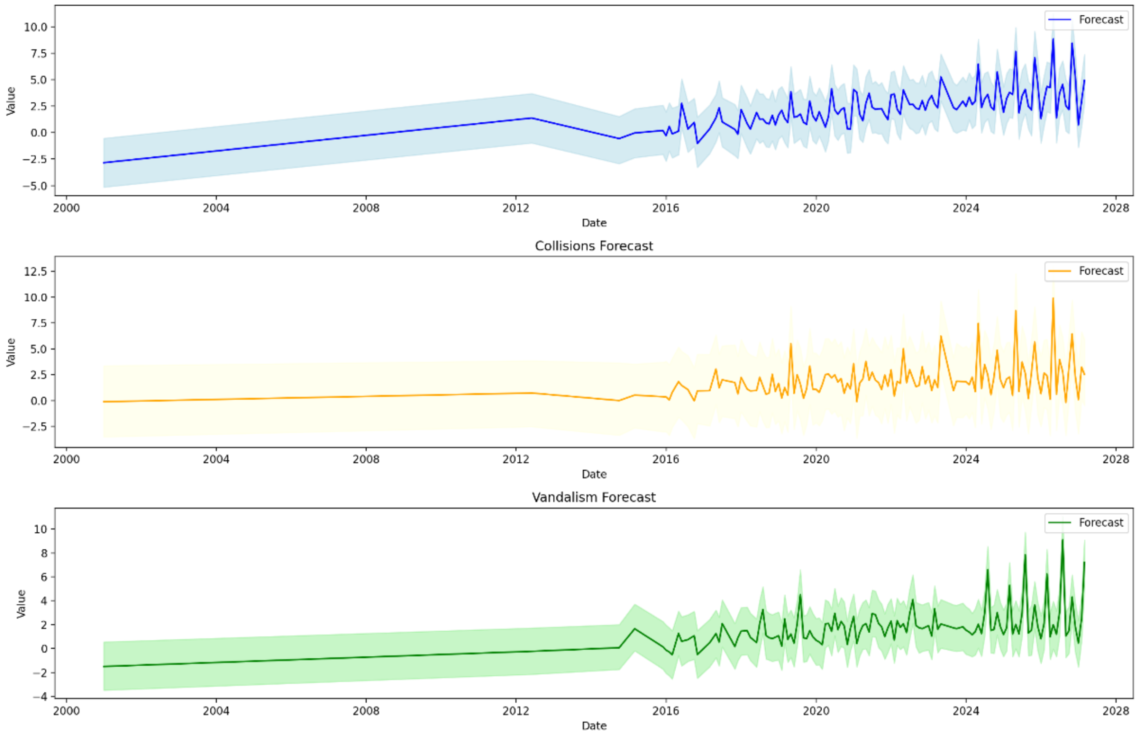

Figure 5: Forecasts

4.1. Mathematical expression of incidents

This research investigated whether the incidents could be understood through mathematical frameworks, specifically by examining the observed relationships between various factors. With a thorough correlation analysis, we could articulate these relationships quantitatively, using linear equations to capture the dynamics at play.

For unscheduled maintenance (U) and collisions (C):

$$U = 0.352C + \epsilon_1 \quad (1)$$

The equation could be understood as (U), which represents a dependent variable or outcome that is being predicted or explained. At the same time, (C) is an independent variable or predictor that influences or helps to explain changes in (U). The coefficient (0.352) indicates the strength and direction of the relationship between (C) and (U). Specifically, this means that, for each one-unit increase in (C), (U) is expected to increase by 0.352 units, assuming that all other factors remain constant. The symbol (ϵ_1) denotes the error term or residual, which accounts for the variation in (U) that cannot be attributed to the predictor (C). This could include random factors, measurement errors, or other variables not included in the equation.

For unscheduled maintenance (U) and vandalism (V):

$$U = 0.269V + \epsilon_2 \quad (2)$$

The incidence of unscheduled maintenance (U) could be closely linked to the frequency of observed vandalism (V) (see equation 2). Specifically, we anticipate a corresponding rise in unscheduled maintenance incidents for every increase in vandalism cases. More precisely, each unit increase in vandalism is expected to lead to an increase of 0.269 in unscheduled maintenance, provided that all other influencing factors remain unchanged. In addition, any variations not accounted for in this relationship are represented by an error term (ϵ_2).

For collisions (C) and vandalism (V):

$$C = 0.455V + \epsilon_3 \text{ (3)}$$

The connection between collision incidents and vandalism could be clarified with Equation 3. This equation suggests that, for each unit increase in vandalism, there is a corresponding rise of 0.455 in collision occurrences, if other influencing factors remain constant. In addition, the equation incorporates an error term (ϵ_3) to account for variability that is not explained by vandalism alone.

4.2. Proposed improvements

The research identified 363 long-standing locomotives and revealed three predominant types of incident: unscheduled maintenance, collisions, and vandalism. Through time series decomposition, seasonal patterns in the frequency of these incidents emerged, indicating significant correlations among the major incident categories [18]. These seasonal trends in train incidents have important implications for operational planning and safety management [19]. One of the key seasonal problems is the impact of weather on rail infrastructure and train operations [19]. For example, extreme temperatures can cause track expansion or contraction, leading to misalignment and an increased risk of derailments. Research indicates that oblique cracks in rail profiles, worsened by temperature fluctuations, can result in rolling contact fatigue, requiring more frequent maintenance and inspections during seasonal transitions [20]. The research highlighted distinct seasonal patterns, particularly in unscheduled maintenance, collisions, and vandalism incidents. There was a marked peak in vandalism incidents in 2019, increased collisions reported in 2022, and heightened seasonality in unscheduled maintenance activities. Understanding these patterns should make it easier to allocate resources better and to implement preventive measures during high-risk periods.

The research exposes an upward trend in incidents since 2016, driven primarily by unscheduled maintenance. This insight should enable railway operators to implement targeted safety protocols and maintenance schedules that align with seasonal risk patterns. Furthermore, the findings underline the need for season-specific operational strategies, as the costs associated with incidents can vary by season and other factors, ultimately enhancing safety planning and resource management.

The study also developed mathematical equations to clarify the relationships between various incident categories, and used the Prophet model for forecasting purposes. This model successfully predicted increases in maintenance issues, collisions, and vandalism incidents, thereby making it easier to manage railway assets proactively. The findings offer valuable insights for creating targeted strategies to reduce incidents and enhance operational efficiency in the railway sector. While the insights presented in this study are both useful and significant, it would be essential for future research to explore the subject matter in greater depth. Such exploration should address and resolve several key issues and questions that have emerged from these findings. Specifically, future investigations should aim to understand the underlying factors contributing to these issues:

A) Impact of incidents on safety and operations
   - What are the implications of unscheduled maintenance incidents for railway service safety and operational efficiency?
   - How do different types of train incident affect the human and economic costs associated with rail operations?

B) Economic consequences of train incidents
   - What is the economic impact of train incidents on railway companies, particularly regarding service disruptions and legal liabilities?
   - How do investment levels in safety training and infrastructure correlate with the frequency and severity of railway incidents?

C) Psychological impact on personnel

- What psychological effects do train drivers involved in critical incidents experience, and how do these impacts affect overall service delivery?
- What support systems are most effective in managing the psychological aftermath of train incidents for railway personnel?

D) Effectiveness of safety training programmes

- To what extent do training programmes focused on emergency preparedness and incident management improve safety outcomes?
- How do trained personnel perform in high-pressure situations compared with untrained staff during incidents?

E) Recommendations for future safety measures

- What strategic recommendations could be made, based on the analysis of incident trends, to enhance railway safety and operational efficiency?
- How could railway companies prioritise incidents that have the greatest impact to improve safety and to reduce costs?

By thoroughly examining these aspects, researchers could provide more comprehensive insights to advance the field.

4.3. Validation and reliability

The results from the Prophet model indicate the following statistics for the three categories, unscheduled maintenance, collision, and vandalism (see Table 2). The mean squared error indicates the average of the squared differences between predicted and actual values [21]. In this case, the model best predicted vandalism with the lowest MSE of 1.0101, unscheduled maintenance at 1.3090, and collision with the highest MSE of 2.6061. This suggests that the model might struggle more with collision data. The mean absolute error reflects the average absolute differences between predicted and actual values, providing a measure of accuracy in the model [22], [23]. Again, vandalism shows the best performance with the lowest MAE (0.5479), followed closely by unscheduled maintenance at 0.5901. The highest MAE is for collision at 0.6696, indicating that this category has more significant prediction errors on average. The R-squared score indicates how well the independent variables explain the variability of the dependent variable [24], [25]. Unscheduled maintenance has the highest R-squared value of 0.4156, suggesting that the model explains 41.56% of the variance in the data. Vandalism has a moderate score of 0.3171, while collision has the lowest score of 0.1881, indicating that the model explains just 18.81% of the variance for collisions, suggesting poorer model performance in this area. In conclusion, while the Prophet model demonstrates a reasonable predictive ability for vandalism and unscheduled maintenance, it shows less reliability when predicting collision outcomes. Adjustments or further model tuning may be needed to improve the accuracy of the collision predictions.

Table 2: Model accuracy

Model	Prophet		
Statistics	Unscheduled maintenance	Collision	Vandalism
Mean squared error	1.3090	2.6061	1.0101
Mean absolute error	0.5901	0.6696	0.5479
R-squared score	0.4156	0.1881	0.3171

5. CONCLUSION

This study examines the primary factors that lead to locomotives in South Africa being classified as long-standing, defined as being out of service for more than 50 days. It also analyses trends in train incidents, focusing on the incident categories that have a significant impact on the number of long-standing assets. The research team gathered data from various depots nationwide, identifying 363 long-standing locomotives. The most common incident types were unscheduled maintenance, collisions, and vandalism. Time series decomposition indicated seasonal patterns in the occurrence of incidents, while correlation analysis revealed significant relationships between the three main incident categories. The Prophet model was used, forecasting an increase in incidents of unscheduled maintenance, collisions, and vandalism. In addition, mathematical equations were proposed to illustrate the relationships among these incident categories. The study underscores the need for further research on the implications of incidents for safety, operations, and personnel and the effectiveness of safety training programmes.

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