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Analysis of the impact of climate-driven extreme weather events (EWEs) on the UK train delays: A data-driven BN approach

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ABSTRACT

Climate change exacerbates the occurrence of frequent Extreme Weather Events (EWEs), directly disrupting railway operations in numerous countries, notably the United Kingdom. Projections for the UK climate indicate an increase in rainfall intensity, warmer and wetter winters, hotter and drier summers, and more frequent and intense EWEs. Such climatic shifts cause increased weather-related railway delays, which in turn result in significant economic loss. This study develops a new risk model using a data-driven Bayesian Network (BN) to analyse the impact of climate-induced EWEs on UK train delays. The model quantifies the influence of various factors on delays, providing deeper insights into their individual and combined effects. The new model and the findings contribute to the disclosure of 1) the interconnections among the different variables influencing train delays, including the origin and destination of the train and traction type, and 2) the prediction of the quantitative extent to which the variables can jointly lead to train delays of different severity levels, incident reason, the month of occurrence, the responsible operator, and the train schedule type. Critical findings highlight the substantial negative impact of severe flooding on the operational reliability of the UK railway system. An important insight was the significant clustering of delays ranging from 80 to 90 min, particularly on Fridays, suggesting the need for targeted operational interventions in specific regions. Additionally, the analysis identified December as the most hazardous month for train delays due to EWEs, with January and July also showing elevated risk levels. This paper offers valuable insights for transport planners, enabling them to prioritise climate-related scenarios causing the most severe train delays and to formulate the associated adaptation measures and strategies rationally.

1. Introduction

Climate change is manifesting through rising global temperatures and increasing greenhouse gas emissions, with significant projected impacts on the UK, including warmer, wetter winters, hotter, drier summers, and more frequent Extreme Weather Events (EWEs). These shifts, as corroborated by studies like those by Binti Sa'adin et al. [1] and Wang et al. [2], are expected to persist, with changes in their temporal and spatial distribution due to prevailing meteorological phenomena. The railway systems and transportation infrastructure are significantly impacted by these climatic variations, facing threats from EWEs that disrupt the integrity and operation of these systems. Factors such as temperature fluctuations, changing wind patterns, and variations in precipitation, among others, contribute to this vulnerability, underscoring the urgent need for strategies to bolster the resilience of transportation systems against climate-induced shifts. For instance, Malaysia's East Coast railway line suffered considerable damage in December 2014 due to severe flooding, disrupting operations for six months. The devastation extended beyond the tracks, affecting signalling equipment and causing the total collapse of a railway bridge in Kemubu, Kelantan [3].

The implications of climate change extend deeply into the UK's railway network, where infrastructural damage from flooding, a consequence of increased precipitation, poses a substantial threat. This

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situation, as detailed by Ludvigsen and Klæboe [4] and Wang et al. [2], could impact up to 71 % of the railway's infrastructural value, with vulnerabilities such as infrastructure embankment failure, and compromised bridge foundations leading to potential collapses and derailments. Moreover, the Met Office anticipates warmer coastal seas and more frequent heatwaves, exacerbating issues like track buckling and signalling failures, which compromise the safety and efficiency of railway operations. These challenges are compounded by the risks posed by storms and high winds, which can obstruct tracks and destabilise vehicles, further stressing the critical need for adaptive measures.

Addressing these challenges necessitates a novel approach to analysing and predicting the impact of EWEs on railway operations. The limited literature on the specific impacts of climate threats on railways underscores the value of a new framework that leverages big data and AI for risk analysis and prediction, as suggested by studies from Binti Sa'adin et al. [3]. This approach is crucial for enhancing rail system resilience and adapting to the evolving climate landscape. By employing big data on UK train delays caused by extreme weather, this study aims to develop an AI-driven model that can accurately assess and predict risks, thereby contributing significantly to railway climate adaptation planning. The systematic approach to improving railway resilience involves collecting and analysing data on railway failures to identify the primary Risk Influential Factors (RIFs), which are variables that significantly affect the likelihood and impact of potential adverse events contributing to delays and shaping the overall risk profile of the railway system. This analysis lays the groundwork for predictive models that forecast risks associated with environmental conditions, emphasising the importance of addressing the lack of literature on failures due to EWEs, particularly using Bayesian Networks (BNs). BNs are used for their ability to capture complex interconnections between RIFs, offering a sophisticated tool for risk analysis in railway systems.

Further advancing this study of using BN in risk analysis, scholars like Wang et al. [5] have integrated fuzzy logic with BNs to refine risk assessment methodologies, addressing the challenges of incorporating subjective data into quantitative models. This innovation points to the critical need for a comprehensive evaluation of methods used in climate risk assessments for railways, especially when dealing with subjective data within BNs. The subsequent research by Wang et al. [6], which utilised a Bayesian deep learning and multilayer perceptron approach, highlights the ongoing effort to bridge the knowledge gap concerning weather influences on railway incidents, underscoring the potential of such methodologies to enhance the understanding of climate impacts on railway infrastructure. However, due to the subjective nature of the data involved, the findings are subject to challenges. Therefore, new research is needed to utilise objective failure data for climate impact analysis in transportation. This paper seeks to fill the gap and makes additional noteworthy contributions, outlined as follows:

(1) A novel data-driven BN model has been developed for analysing train delays, enabling a comprehensive risk analysis for train delays in the UK. The model utilises train delay data to establish benchmarks for regional railway analyses.
(2) A dataset capturing train delays from 2022 to 2023 is compiled from Network Rail, laying the foundation for an innovative delay database. This database systematically classifies incident causes resulting in delays, categorising them based on different RIFs.
(3) The integration of all Network Rail-regulated RIFs into a novel data-driven BN-based risk analysis model enhances the precision of predicting and diagnosing train delay risks.
(4) A notable contribution lies in the capability to scrutinise delays surpassing 60 min, exclusively linked to EWEs conditions across the entire UK train.

The structure of this paper is organised as follows: Section 2 provides an in-depth review of the literature, covering climate change projections in the UK, railway failures attributed to climate impacts, and the current advancements in the use of BN for risk analysis in railways. Section 3 details the methodology employed, including data collection processes and the identification of RIF. Section 4 discusses the findings and results, encompassing the BN model's structure, development, evaluation, sensitivity analysis, and implications. Section 5 concludes the paper with and outlines directions for future research.

2. Literature review

2.1. Climate change projections for the UK

The investigation into the impacts of climate change on transportation infrastructure and operations has witnessed global attention. However, a noticeable gap exists in the literature addressing the specific implications for the UK railway network, warranting further exploration. In contrast to broader trends observed in other regions, delayed data analysis in the UK unveils a distinctive vulnerability, where heatwaves exert minimal impact compared to the prevalent risks of floods and heavy precipitation. In the complex fabric of the UK's climate, significant year-to-year rainfall variations underscore the importance of recognising enduring natural fluctuations. According to the latest report from the Met Office, the country has seen a consistent rise in precipitation over recent decades, with the period 2011–2020 being notably 9 % wetter than the baseline of 1961–1990 [7].

Drawing upon high-resolution regional model datasets and observational data reveals a pronounced surge in extreme rainfall totals across the UK, which is ascribed to anthropogenic climate change [8]. The occurrence of significant flooding events during the winters of 2013/14, 2015/16, and 2019/20, coupled with incidents in the autumn of 2000 and the summer of 2007, highlights the escalating frequency of such events. An examination of UK rainfall extremes from 1961 to 2000 unveils regional variations, notably with substantial increases in 5- and 10-day annual maxima in the western and northern regions, contrasted by marginal decreases in the southern UK. It is essential to acknowledge the spatial variations in rainfall alterations, where Scotland witnesses a notable escalation while the southern and eastern areas of England undergo more subtle changes. This intricate understanding of how climate change impacts the UK railway network assumes paramount significance in facilitating informed decision-making and devising proactive adaptation strategies amidst the evolving intricacies of climatic patterns [9].

Within the changing climate landscape, the Met Office reports a notable warming trend in the United Kingdom, indicating an approximate temperature increase of 1 °C since the 1950s. This transformative shift extends not only over terrestrial areas but also encompasses the coastal seas surrounding the UK, contributing to a comprehensive understanding of the broader environmental impact. Within this context, the manifestation of longer and more frequent warm and hot spells becomes apparent. The Met Office underlines the gravity of these climatic alterations, providing a comprehensive understanding of the changing thermal dynamics in the UK [7]. A striking illustration of the tangible repercussions of such temperature variations unfolded during the summer of 2018. In the summer of 2018, an extended spell of intense heat and dry conditions created disruptions in various transportation sectors, notably affecting the rail network. In response to the elevated temperatures, the rail industry grappled with challenges such as the risk of rail buckling and signalling complications. To mitigate these risks, speed restrictions were imposed on numerous rail lines, a measure essential to ensuring the safety and integrity of the rail infrastructure [10]. These incidents underscore the vulnerability of critical transportation infrastructure to the effects of climate change, emphasising the necessity for adaptive strategies and a profound comprehension of climatic details to fortify the resilience of the UK railway network.

2.2. Weather-related delays in rail transport

In the UK, the tangible evidence of climate change is unfolding, showcasing an anticipated escalation in severity and prevalence due to the rising trajectory of greenhouse gas emissions and global temperatures. The United Nations Intergovernmental Panel on Climate Change (IPCC) asserts that these anticipated climatic shifts are expected to impact all modes of transportation to varying degrees [11]. Such changes are manifested through diverse effects, including shifts in precipitation patterns and heat stress, which pose risks to water supplies, localised flooding, particularly in coastal regions, and human health. The UK's current climate trajectory, indicating a trend towards warmer and wetter winters, coupled with hotter and drier summers, presents specific challenges for the transportation sector by increasing the likelihood of extreme weather events, such as flash floods, impacting transport infrastructure [12].

Adverse weather conditions, including extreme cold that leads to snow and ice accumulation on tracks, challenge the UK's rail infrastructure, potentially causing significant delays. Furthermore, the development of ice on electrified third rails and overhead power cables can hinder trains from accessing essential power, leading to immobilisation. Elevated temperatures also disrupt railway operations by prestressing UK rails against high temperatures, with a stress-free temperature set at 27 degrees Celsius, indicating that rail temperatures may soar by up to 20 degrees when air temperature reaches 30 °C. Exceptional weather conditions, including temperatures below −5 °C or above 30 °C, storm winds causing physical damage, snow exceeding a depth of 15 cm, or rainfall surpassing 150 mm in 24 h, further challenge the resilience of the system. The existing railway network, incorporating modern concrete sleepers, is strategically designed to counteract steel rail expansion and contraction under diverse weather conditions, effectively containing forces from temperature-induced rail movements to prevent track buckling [7].

Performance metrics employed by Network Rail, such as the Public Performance Measure (PPM) and the Moving Annual Average (MAA), reflect the operational impact of these weather challenges. Recent data reveals a decrease in national PPM, underscoring the adverse effects of climate change on railway punctuality and reliability. Additionally, the National Rail Passenger Survey (NRPS) provides insights into passenger satisfaction, further emphasising the impact of weather conditions on rail service performance [13]. The performance of train operators may be directly or indirectly impacted by these adverse weather conditions, leading to disruptions in the railway infrastructure. A study on The Netherlands' railway network revealed that snow, extreme within-day temperature variations, and exceedingly high temperatures could lead to network segment closures and potential delays. Furthermore, the escalation in heavy precipitation and more frequent high winds raises significant concerns for network operators [14]. Coastal flooding and storm surges, associated with rising sea levels, present imminent threats to transport infrastructure in low-lying maritime areas, while increased precipitation levels have the potential to worsen congestion and elevate the frequency of traffic incidents [6]. Recent incidents underscore the urgent need to address the impacts of climate change on transportation infrastructure. For instance, the heavy snowfall reported in DAB022 (incidents involving snow) necessitated reductions in train speeds for safety, causing considerable train delays. Similarly, DAB019 (incidents involving trees) documents how storms can cause trees to fall onto tracks, disrupting train services. These incidents demonstrate how extreme weather directly affects the safety and efficiency of transport [7].

Recent studies spotlight the escalating impact of climate change on transport infrastructure, particularly railways. Abdel-Mooty et al. [15] investigate the increased vulnerability of railway bridges in southeast England to scour, a risk intensified by changing hydrological conditions driven by EWEs. Complementing this, Sun et al. [16] develop an optimisation method for post-disaster recovery in electrified railways, enabling dynamic prioritisation of repairs to minimise operational losses. Expanding on this theme, further research should assess climate-related risks in port operations by integrating hazard modelling with economic analysis to strengthen resilience planning for these critical transport hubs. These insights underline the necessity of integrating climate risk assessments into strategic management across railways and related infrastructure [15,16]. A study encompassing Norway, Sweden, Switzerland, and Poland has revealed that adverse weather conditions significantly contribute to delays in rail freight operations, disrupting the continuity of European rail infrastructure. This in-depth analysis emphasises the urgent need for adaptive strategies to lessen the effects of weather events on railway systems [14]. It highlights the crucial role of identifying Key Risk Indicators (KRIs) that delineate the impact of risks on rail network operations. These KRIs are essential for understanding how specific risks affect different areas of railway operations and their potential consequences. Table 1 further delineates these implications, illustrating the potential effects of weather events on railway systems through KRIs, thereby underscoring the need for targeted interventions to mitigate risk and enhance system resilience.

Table 1
EWEs impact on rail network.

EWEs	KRI	Impact on the rail network	References
Flooding & Heavy precipitation	Track inundation. Signal system malfunction Drainage system failure Delayed journey times	1) Loss of control and traction; 2) Pressures on tyres and components of vehicles; 3) Reduced speed; 4) Uneven or break braking; 5) Roadbed erosion; 6) Train delays from flooded tracks.	[4]
Storm &Wind	Fallen debris Power outage Infrastructure damage	1) Potential for fallen trees obstructing railway lines; 2) Damage to overhead power lines causing power outages; 3) Structural damage such as bridges and tunnels; 4) Railroads blocking; 5) Train delays.	[17]
Snow & Ice	Reduced traction Ice accumulation Blocked track lines Reduce network traffic Damaged freight Network blockages and power supply disruptions	1) Reduced traction on tracks leading to slower train speeds; 2) Increased risk of points and switches freezing; 3) Wheel axles break causing the weight of snow; 4) Frozen temperature-sensitive goods; 5) Reduced visibility; 6) Train delay.	[18]
Heatwave	Infrastructure damage Track buckling Operational disruptions Electrical system overload	1) Derailment; 2) Reduced rail speeds; 3) Increased strain on electrical systems and cooling systems; 4) Disruption to passengers due to overheating on trains; 5) Problems for temperature-sensitive goods; 6) Train delay.	[3,17]
Fog	Service interruption Reduced visibility Signal visibility	1) Reduced visibility leading to slower train speeds; 2) Difficulty in reading signals; 3) Risk of damage and collision; 4) Train delays from reduced visibility.	[18]
Lightening	Power surge System disruption Fire hazard Infrastructure damage	1) Risk of electrical equipment damage due to lightning strikes; 2) Disruption of signalling and communication systems; 3) Train delay.	[8]

2.3. The application of BN in railway risk analysis

BNs, fusing the principles of graph theory and probability theory, serve as a robust framework for modelling the probabilistic interdependencies among variables. These networks are depicted as acyclic-directed graphs, where nodes represent random variables, and arcs signify direct probabilistic relationships. The foremost goal in the field of BN structure learning is to delineate these dependencies, culminating in the formation of a Directed Acyclic Graph (DAG) [19,20]. Conceptually, BNs stand out as sophisticated tools, both graphically and analytically, adept at encapsulating complex systems. They enable the graphical depiction of diverse components, which interact through conditioned probabilities, thus demonstrating remarkable versatility in addressing the complexities inherent in multifaceted systems [21]. BNs are particularly esteemed for their ability to manage the interplay between actions, knowledge, and uncertainty within a system, showcasing their proficiency in learning the structure and parameters of system data, thereby accentuating their analytical capabilities [22,23]. Remarkably, BN analysis has been distinguished for its efficacy in accounting for interactions among EWEs, offering a more holistic comprehension relative to other statistical methodologies.

An in-depth review of existing literature reveals that while BNs have found applications within the railway sector, the research volume is considerably less extensive compared to other transport domains. This scarcity becomes even more pronounced when examining the application of BNs in addressing failures prompted by climate change-driven EWEs, highlighting a significant research gap in the field. For instance, Chen et al. [24] underscores the influence of EWEs on high-speed railway delays, pinpointing device failure as a crucial determinant. Similarly, Cotterill et al. [8] employ BNs in developing predictive models for safety incidents within railway operations, aiming to elucidate significant impact factors. The versatility of BNs is further evidenced in various scholarly undertakings. Li's work on assessing the structural safety of railway bridges using BNs showcases the method's bidirectional reasoning and sensitivity analysis prowess [10]. Moreover, a distinct approach to modelling the probability of failure in railway turnout systems under varying weather conditions reflects BNs' unique application breadth [2]. Contrastingly, in another study, they integrate Interpretive Structural Modelling with BNs for a comprehensive analysis of the railway dangerous goods transportation system, reflecting a multi-methodological approach to understanding complex system dynamics [25].

The application of BNs extends to operational risk analysis in railway freight management through integration with Fuzzy Fault Tree Analysis [26] and to the design optimisation for mitigating electromagnetic interference in rail tracks [27]. Furthermore, the use of BNs in evaluating safety management systems within railways in Great Britain and Italy underscores their applicability in dissecting critical factors and relationships impacting front-line performance. The development of algorithms for accident prediction at railway crossings illustrates the methodological advancements in BN applications, enhancing predictive accuracy through diverse knowledge integration [28]. In a recent study [24], a Data-Driven Bayesian Network (DDBN) was developed to analyse freight railway accidents across varied scenes. This novel approach, achieving an inference accuracy of 87.92 %, utilises an unsupervised-supervised method for defining node states and a causal ordering algorithm, significantly improving the predictive accuracy and the applicability of safety measures in specific accident contexts. However, its effectiveness is limited to scenarios where detailed scene-specific data is available.

Yet, despite these advancements, the exploration of BNs in addressing railway failures, especially those induced by climate change, remains underexplored. This gap, particularly in the context of the UK railway system's vulnerability to changing climate and EWEs, underscores the urgent need for further research. This paper seeks to bridge this gap by presenting a comprehensive analysis of factors leading to train delays, leveraging a novel dataset developed from Network Rail's incident database for the period 2022 to 2023.

3. Methodology

Within the realm of probabilistic modelling, BN emerges as a distinctive entity, a dynamic DAG. Its intricate composition involves nodes, each interconnected by links that delineate variables and the intricate web of influences they exert on one another. In this BN methodology, a systematic approach unfolds through four distinct steps, each delineated by specific subsets. The first step is dedicated to comprehensive data preparation, involving a thorough process of data collection and preparation procedures. Following the careful cleaning of incomplete entries and a discerning screening of the Network Rail dataset, the journey proceeds to the second step, a pivotal phase centred on model development. Herein, the BN model takes shape, leveraging the refined dataset with precision and purpose.

In the domain of model validation, a dual-pronged strategy is implemented. The first aspect unfolds in a sensitivity analysis, deploying three crucial indices, mutual information, joint probability, and True Risk Influence (TRI) to thoroughly examine the model's sensitivity to varying conditions [29]. Simultaneously, the second aspect comprises model evaluation, anchored by four pillars: a stringent model correctness verification process, practical application through predictive operations with real case data, scrutiny of the model's internal consistency, and pivotal real case verification. This multi-dimensional model validation process not only ensures a detailed understanding of the model's intricacies but also fortifies the credibility of the study's outcomes. In weaving this comprehensive methodology, the paper establishes a robust foundation for deriving meaningful insights from the BN model developed. Fig. 1 illustrates the detailed methodology, outlining each step comprehensively.

3.1. Data collection and processing

The study utilised a singular dataset from Network Rail's open data feeds, "Delay Attribution Data." This dataset integrates detailed reports of incidents that cause train delays, including TRUST TRAIN IDs. These IDs are critical for linking delay incidents to actual train performance monitored by the TRUST system, which tracks train performance against scheduled timetables. The TRUST system enhances dataset reliability by enabling the verification of reported delay incidents against documented train performances, ensuring the accuracy of delay attributions. The attribution database from Network Rail categorises incidents affecting train delays into specific groups, with a particular focus on those induced by EWEs. This categorisation facilitates a targeted analysis of the impacts these factors have on train operations. Initially, the dataset contained comprehensive entries for each incident during the specified period. Through a systematic process of screening, cleaning, and categorisation based on criteria such as relevance to EWEs, completeness of data for all RIFs, and severity of delays (exceeding 60 min), the dataset was refined. This process reduced the initial 6100 entries to 1530, which were further analysed. For this study, the dataset spanning the financial year 2022–2023 was selected to ensure the analysis reflected the most current operational conditions and incorporated the impact of all seasons on train delays. This period provides a holistic view of the yearly operational dynamics, which is essential for a comprehensive analysis.

Network rail attribution database: This dataset provides exhaustive incident reports that are crucial for identifying specific causes of train delays. These detailed records are instrumental from the initial analysis stages, offering insights into the diverse impacts of severe weather on train operations.

TRUST data: While the analysis leverages data from the Network Rail attribution database, the dataset includes TRUST TRAIN IDs, which reference the TRUST system that tracks actual train performances

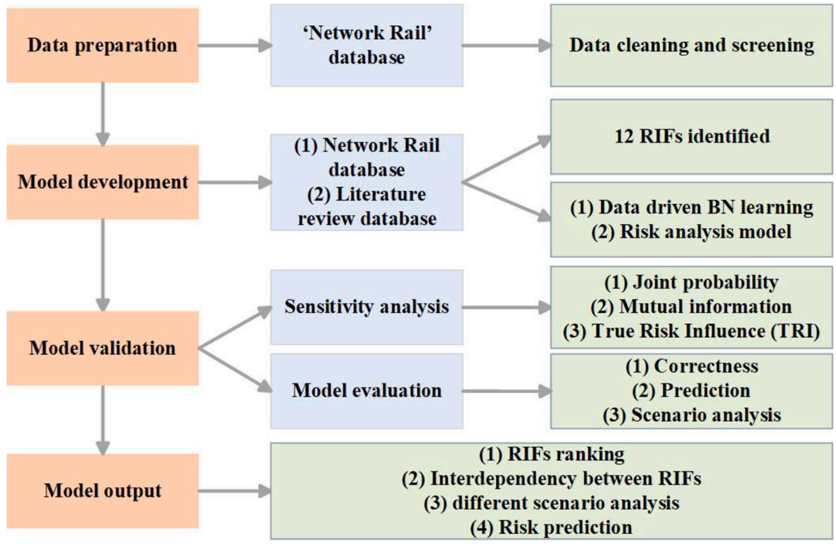

Fig. 1. Detailed methodological framework.

against scheduled timetables. This inclusion helps to quantify the operational impacts by correlating reported incidents with actual service disruptions, thus providing a comprehensive view of the operational consequences of delays.

Data source: The analysis utilises a specific dataset from Network Rail's open data feeds titled "Delay attribution data", which contains all attributed delays to passenger train services. This dataset is enhanced by the inclusion of TRUST TRAIN IDs, enabling a deeper analysis of the probabilistic relationships between weather events and resultant train delays. The TRUST TRAIN IDs are inherently included within Network Rail's delay attribution data. This approach simplifies the analytical process and maintains the integrity and reliability of the data by using a single, comprehensive source.

3.1.1. *Data cleaning and data screening*

While examining 6100 data entries, it became apparent that specific information related to the traction type of trains and their destinations was absent. They safeguarded the coherence of the dataset by systematically excluding incomplete entries and thoroughly inspecting each remaining record, effectively eliminating inaccuracies or irrelevant data. Another crucial aspect of this process involved considering data related to delays of 60 min or more by following the worst-case principle in safety science, while entries with durations less than this threshold were removed from the final database. This comprehensive approach ensures the reliability and relevance of the dataset for further analysis, adhering to robust data cleaning and screening practices.

Following a comprehensive examination focused solely on delays attributed to severe weather conditions, this meticulous process resulted in a final dataset comprising 1530 entries. This refined dataset serves as a more accurate and targeted foundation for subsequent analysis and interpretation. Importantly, by focusing exclusively on significant delays caused by EWEs, the study isolates a critical variable, allowing for a more sophisticated understanding of its impacts on train operations. This strategic approach to data refinement effectively facilitates the identification of trends and patterns that are vital for developing resilient train scheduling and operational strategies under adverse weather conditions. Furthermore, eliminating less impactful data points ensures a streamlined analysis, increasing the overall efficiency of the research process and ensuring that conclusions drawn are statistically significant and practically applicable in real-world scenarios.

3.1.2. *Network rail data*

Recorded through the Train Running Under System (TRUST), delays to scheduled train services on the Great Britain (GB) rail network are carefully documented. The system compares actual train movement events with the planned schedule, providing a comprehensive insight into delays. This process not only records delays but also offers explanations for their causes. The collected data contributes to an incentive scheme aimed at reducing delays. Examining each rail incident on the network in-depth reveals a wealth of information. This comprehensive dataset includes details such as date, time, location, origin, destination, the reason for the delay, responsible company, traction type, schedule plans, and the total delay incurred measured in minutes. Network Rail employs various factors to explain incidents, categorising them based on weather conditions such as snow, ice, earth slip, wind, flooding, fog, heat, lightning, severe weather, and wind. These categories align with the guidelines outlined in the Delay Attribution Principles and Rules [7]. The dataset spans from April 2022 to March 2023, encompassing incidents throughout each month. The RIFs encapsulate the key attributes, including Daytime, Weekdays, Months, Years, Planned Origin, Planned Destination, Attribution Status, Incident Reason, Responsible Operator, Application Timetable, Train Schedule, Traction Type, and Event Type. As established in the literature review [30], daytime is stratified into two subsets: day (06:00–18:00) and night (other), while Weekdays incorporate all days of the week. Months consist of the standard twelve, and Years span 2022 and 2023. Planned Origin and Planned Destination pinpoint the commencement and destination locations of the journey, distributed across 14 distinct regions throughout the UK.

Attribution Status denotes the incident's official acceptance process status, with 'Agreed, ' 'Disputed, ' and 'Waiting for Acceptance' delineating ongoing investigations. Incident Reasons are categorised into many different groups, but the data here are refined to exclusively include those rooted in severe weather for this study. Responsible Operators, constituting 14 distinct roles corresponding to various regions in the UK. Application Timetable distinguishes between the official performance records (N) and short-term replacements, typically representing the reinstatement of part of a cancelled service. The train schedule includes Long Term Plans (LTP) and Short-Term Plans (STP). The dataset includes a Traction Type variable, which categorises railway propulsion into nine groups: Diesel locomotive (D), Diesel Multiple Unit (DMA), Diesel Multiple Unit with Electric Transmission (DME), Diesel Multiple Unit with Mechanical Transmission (DMS), Diesel Multiple Unit (DMU), Electric locomotive (E), High-Speed Train (HST), and Light rail (L). The cross-referencing process leans heavily on records manually verified from the Network Rail website, a public repository housing the UK's railway code systems. To facilitate compensation payments among industry stakeholders in case of delays, the data collected ensures a reliable attribution of total delay values to each incident.

3.2. RIFs identification

RIFs were selected based on a comprehensive approach that involved both an extensive review of the literature and an empirical analysis of delay data. Initially, a systematic review of relevant peer-reviewed articles from the Web of Science was conducted, focusing on publications from 2010 to 2023 with keywords such as 'Bayesian network' and 'railway failures. This literature review aimed to identify prevalent factors that influence railway operations during EWEs. Concurrently, data from the Network Rail attribution database were analysed to categorise delay incidents under various weather-related factors, ultimately resulting in the identification of 11 RIFs. Eight of these RIFs were consistent with the literature, while three were derived directly from the attribution data, with severe weather being a particularly significant factor.

The selection of RIFs was guided by three main criteria to ensure their relevance and reliability relevance to train delays under extreme weather, the availability of consistent and comprehensive data throughout the study period, and statistical validation to verify their significance. Each factor underwent statistical testing to establish its influence on train delays, thereby ensuring empirical support for its inclusion. By combining insights from literature with real-world data, this study aims to provide a robust and validated set of RIFs that significantly impact railway safety and performance during extreme weather conditions. This comprehensive approach contributes to enhancing the robustness of the Bayesian Network model used in this analysis. Fig. 2 presents the distribution of the identified RIFs based on a review of the existing literature.

In Table 2, a comprehensive compilation of RIFs from literature and database sources is presented, resulting in a synthesis of 13 factors. Among these, a notable convergence is observed in five factors: flood and precipitation, snow, ice, lightning, and heat waves, all categorised under the incident reason node. The additional RIFs, including months, daytime, and weekdays, are also recognised as factors recurring in both the literature review and the database. The database categorises severe weather into five distinct types, each uniquely impacting different structural components of the railway system. Specifically, flooding predominantly affects track components, leading to washouts and the destabilisation of the ballast, which compromises track stability. Extreme heat frequently causes rail buckling due to thermal expansion, a particular risk in continuously welded rails where expansion has limited free space. Heavy snow and ice pose significant risks by inducing mechanical failures in switches and creating signal errors due to the accumulation of ice, which interferes with normal operations. High winds are notorious for causing failures in overhead line equipment and can dislodge branches or debris onto the tracks, posing serious risks to train movement and safety. This detailed approach allows for a more comprehensive understanding of severe weather implications. The intersections and disparities within these RIFs emerge as a pivotal contribution within the scope of this paper. It leads to the development of an in-depth BN-based model for comprehending train delay risks. Importantly, the integration of real data provides an intricate representation without constraints. This innovative methodology not only advances the development of a robust train delay risk model but also underscores the richness of real-world data in contributing detailed insights to the discussion.

In constructing a comprehensive model to analyse risk factors within the railway network, the proposed BN approach hinges on a reasonable selection of RIFs based on the prevalence in the Network Rail database and their demonstrable impact, as reflected in the literature. While the literature review is instrumental in informing potential risks, the ultimate inclusion of these factors in the new model is determined by a combination of their recorded incidence, the magnitude of their influence on railway operations, and the practicality of their mitigation. For instance, despite the presence of multiple literature references supporting wind as a RIFs, its exclusion from this investigation is deliberated upon its relative infrequency within the database, the potential for lesser impact on service disruptions, or the efficacy of existing infrastructure resilience to wind-related events. This discerning approach ensures that the model maintains a focused scope, directing resources and analytical efforts towards RIFs with the most substantial evidence of impact on the railway network in the UK, ensuring a balance between theoretical risk factors and empirical data-driven insights.

The model's integrity is reinforced by a balanced consideration of RIFs drawn from detailed literature reviews and real-world databases, such as Network Rail's. This dual approach ensures that while the new model is informed by rich global research, it remains grounded in tangible data that reflects the day-to-day realities of railway operations. Several studies utilising Network Rail data highlight the importance of various RIFs in railway delay analysis. For example, Reynolds and Maher [39] and Jaroszweski et al. [40] identify critical RIFs, particularly incident reasons such as weather-induced disruptions, which play a significant role in delay propagation. Building on this shared focus, our work uniquely incorporates a broader set of RIFs that have not been comprehensively explored in previous UK-based studies, contributing a novel perspective to railway risk assessment.

This process guarantees that the risk analysis is not only reflective of Network Rail's specific context but also holds value for the railway sector at large. Through this methodology, each RIF is thoroughly vetted to determine its true relevance to the operational resilience and safety of railways, assuring that the new model remains relevant and adaptable for various infrastructural needs and challenges [41]. Ultimately, Table 3 presents the definitions and statuses of all RIFs explored in this study. All the definitions and statuses are derived from the UK Network Rail reports.

All these RIFs significantly influence train delays, which function as the target node. To capture a comprehensive spectrum of scenarios, the

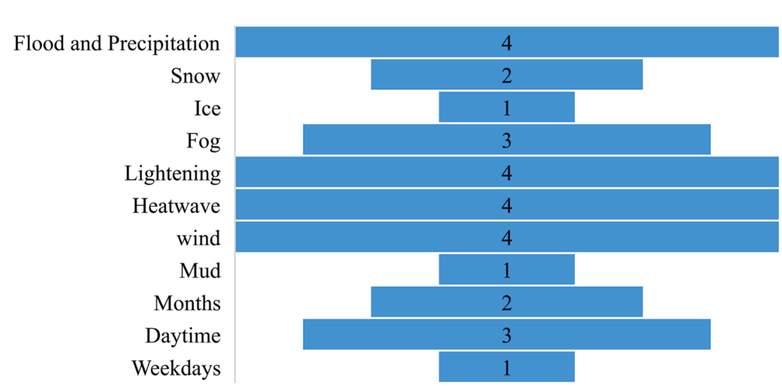

Fig. 2. Distribution of identified RIFs in the literature.

Table 2
Comparative analysis of EWEs: literature review vs. network rail database.

		Risk factors												
References	**Methods**	**F1**	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**	**F9**	**F10**	**F11**	**F12**	**F13**
[31]	BN	✓	✓	✓	✓		✓				✓			
[32]	BN								✓					
[25]	BN					✓	✓					✓		
[33]	Bayesian hierarchical							✓						
[34]	BN								✓				✓	
[35]	Dynamic Hybrid Model												✓	
[36]	Statistical regression models											✓	✓	✓
[24]	BN	✓	✓			✓	✓		✓					
[37]	BN	✓				✓			✓					
[38]	Fragility Modelling	✓					✓							
Network Rail	Source: Network Rail Open Data Reports	✓	✓	✓		✓	✓	✓		✓		✓	✓	✓
Total		5	3	2	1	4	4	2	2	1	1	3	4	2

Note: F1: flood and precipitation, **F2:** snow, **F3:** ice, **F4:** fog, **F5:** lightening, **F6:** heatwave, **F7:** severe weather, **F8:** wind, **F9:** leaf contamination, **F10:** mud, **F11:** months, **F12:** daytime, **F13:** weekdays.

Table 3
Definition and status of RIFs.

RIFs	Definition	States
Daytime	Day (06:00 to 18:00), night (other)	Day, Night
Weekdays	Days of a week	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday
Months	The month that the delay occurred in	1,2,3,4,5,6,7,8,9,10,11,12
Years	The year that the delay occurred in	2022, 2023
Planned origin	The location where trains start the journey	Anglia, Central, East Coast, East Midlands, Kent, North & East, North West, Other, Scotland, Sussex, Wales, Wessex, West Coast South, Western
Planned destination	The location where trains end the journey	Anglia, Central, East Coast, East Midlands, Kent, North & East, North West, Other, Scotland, Sussex, Wales, Wessex, West Coast South, Western
Attribution status	Acceptance process for each delay	Attribution Agreed, Attribution Disputed, Waiting Acceptance
Incident reason	Cause of delay	Ice's Impact on Conductor Rail/OHLE (1), Leaf Contamination (2), Lightning Strike's Impact on Unprotected Assets (3), Lightning Strike's Impact to Protected Systems (4), Severe Flood (5), Severe Heatwave (6), Severe Snow or Ice Causing Points Failure (7), Severe Snow or Ice Impact on Infrastructure (8), Severe Weather (9), Severe Weather Impact on Infrastructure (10), Severe Weather Mandating Blanket Speed Restrictions (11), Severe Weather's Impact on Bridges, Tunnels, and Buildings (12)
Responsible operator	Who within the industry is responsible for the delay	Anglia, Central, East Coast, East Midlands, Kent, North & East, North West, Other, Scotland, Sussex, Wales, Wessex, West Coast South, Western
Application timetable	Official performance records	No (N), Yes (Y)
Train schedule	classification of a train service schedules	Very (V) STP Base, very (V) STP Overlay, LTP
Traction type	The model of train propulsion	Diesel locomotive (D), Diesel Multiple Unit (DMA), Diesel Multiple Unit with Electric Transmission (DME), Diesel Multiple Unit with Mechanical Transmission (DMS), Diesel Multiple Unit (DMU), Electric locomotive (E), High-Speed Train (HST), and Light rail (L).
Event type	Whether the train has been delayed or cancelled	C (full cancellation), M (delay), Other (failure to stop, scheduled cancellation, part cancellation)

delays are categorised into five groups: A, B, C, D, and E, depending on their lengths in terms of minutes (Table 4). The discretisation of train delay times in this study is methodically aligned with both regulatory frameworks and the granular analysis requirements of BN modelling. The decision to use a 60-min threshold for categorisation is grounded in UK railway regulations, which mandate refunds for delays exceeding this duration. This operational benchmark is not only a regulatory requirement but also represents a significant threshold beyond which passenger inconvenience markedly increases, making it a critical point for analysis.

Further refining the temporal resolution to 10-min intervals is substantiated by the need to align the delay categorisation with the high resolution of meteorological data. Such fine granularity captures the rapid variability typical of climatic factors, enabling the model to reflect more accurately the immediate impacts of short-duration weather phenomena. This resolution aligns well with the operational time frames within which real-time decisions are made in railway operations, ensuring that the data is actionable and relevant. Preliminary analysis reinforced this choice, indicating that larger intervals obscured critical variations in delay causation and impacts, thus diminishing the model's predictive accuracy and operational applicability. These finer intervals enable the model to better capture subtle variations in delay patterns, which is crucial for implementing effective resource allocation and mitigation strategies during adverse weather conditions. Table 4 below indicates the periods in different groups.

3.3. Navigating BN configurations and TAN modelling

In building the BN model for this study, identifying RIFs was a key step that came after carefully cleaning the data. These RIFs become the main nodes in the network, representing the variables that can affect train delays. Each node is connected to probabilities that show how these variables might influence one another. This paper uses an effective approach to showing how these factors work together to cause train delays in the UK rail network. The Naive Bayes Network (NBN) starts with a basic assumption: all the features looked at are independent of each other once the class is known. However, this assumption doesn't always hold up because it ignores more complex relationships [19]. Tree Augmented Naive Bayes (TAN) which can address the strong assumption

Table 4
Delay classification.

Delay categorisation	Minutes
A	$60\leq t<70$
B	$70\leq t<80$
C	$80\leq t<90$
D	$90\leq t<100$
E	$t\geq 100$

embedded in NBN, was chosen in this work. The TAN model builds on the NBN by adding connections between features to form a tree structure [19]. This is important because it lets us see not just if features relate to delays, but also how they relate to each other. The TAN model thus provides a more sophisticated and detailed representation of inter-variable relationships, especially within the context of classification tasks [11].

3.4. Sensitivity analysis

Sensitivity analysis provides insights into the uncertainty and variability within the BN, aiding in decision-making and risk assessment. This method is used to evaluate the impact of changes in the input variables on the model's output or predictions. This methodology reveals the RIFs that significantly impact the target variable 'train delay'. The analysis employs three crucial methods: mutual information, joint probability, and True Risk Influence (TRI). Beginning with mutual information, this assessment helps better understand how one variable acquires information from others. It measures how two variables depend on each other, indicating their connection and influence, where a higher value signifies a more substantial correlation, indicating a heightened impact on the target node. Moreover, joint probability represents the simultaneous occurrence of multiple events or states in the train delay network [35].

This method can quantify the likelihood of observing a particular combination of values across multiple random variables in the system. Within the BN framework, where nodes indicate diverse variables and edges present probabilistic relationships, the joint probability distribution acquires the comprehensive likelihood of all potential variable configurations. Notably, this relates specifically to the target variable, train delays. Effectively determining the sensitivity of multiple variables is achieved by utilising the TRI method. The subsequent sensitivity analysis reveals the ranking of influences that various variables impose on train delays, determined by their respective TRI values. The magnitude of TRI functions as an indicator, with higher values signifying a more pronounced impact of the associated RIFs on the target node.

3.4.1. Mutual information

Mutual Information serves as a quantifiable metric that reveals the extent of interdependence or shared information between two random variables and quantifies the information acquired about one variable from the knowledge of others. The uncertainty of a variable can be reduced by acquiring knowledge of another variable and can be measured by mutual information. In mathematical terms, the mutual information I $(X; a_i)$ for TBN is displayed below [37,38].

$$I(X; a_i) = \sum_{x,i} p(X, a_i)\ log_b \frac{p(X, a_i)}{p(X)p(a_i)} \tag{1}$$

Where $I(X; a_i)$ represents the mutual information between the train delays, denoted by the variable X and the i^{th} state of the RIFs, represented as a_i. $p(X; a_i)$ is the joint probability distribution function that represents the likelihood of simultaneously observing the train delay X and the state a_i of the RIFs.

3.4.2. Joint probability

The joint probability distribution is a foundational concept that captures the likelihood of all possible combinations of values for variables within a network [42]. Deriving the joint probability involves defining variables, establishing their relationships in a DAG, assigning conditional probabilities, and then combining these probabilities using the chain rule. This process, commonly known as the 'chain rule' allows for a systematic exploration of the detailed effects of RIFs on 'train delay' for the most critical variables identified through mutual information calculations. Joint probability distributions are critical in this analysis because they allow us to understand the likelihood of various combinations of risk factors leading to train delays. This study uses joint probability to quantify the interplay between multiple variables, such as weather conditions, day of the week, and track conditions, and how these factors collectively impact the probability of train delays. This comprehensive view helps to pinpoint which combinations of factors are most likely to cause significant delays, thereby providing actionable insights for railway operators. Moreover, by incrementally increasing each variable's probability state to 100 %, it is possible to observe the relative influence of each factor on train delays. This approach enables us to model the potential impact of each variable in isolation and in combination with others, which is particularly useful for planning preventive measures and for strategic decision-making.

3.4.3. True risk influence (TRI)

True Risk Influence (TRI) and State-Related Influence Factor (SRIF) are key metrics for evaluating variables within BNs, particularly in risk assessment scenarios. TRI quantifies the influence of specific factors on outcomes, providing insight into which variables critically affect the network's behaviour. TRI is calculated by identifying scenarios where the risk of delay is notably high (High-Risk Inference (HRI)) and notably low (Low-Risk Inference (LRI)), allowing us to determine the sensitivity and potential impact of each RIF. This method ensures an intuitive understanding of central tendencies in risk levels, suitable for decision-makers across various disciplines [43,44].

This quantification is crucial for prioritising mitigation efforts effectively within the railway network [6]. For example, in train delay analysis, TRI helps prioritise factors for effective risk mitigation. In this case, delays between 60 and 70 are designated as 'A'. Focusing on a specific factor, such as the incident reason, the highest amount is (30.3) and the lowest (11.8) probabilities for 'A' are found. The actual mutual information for incident reason in scenario 'A' is 3.53. To determine TRI covertly, both the highest and lowest probabilities are subtracted from 3.53, the results are added, and then the total is divided by 2. The equation of TRI is provided below.

$$TRI = \frac{HRI + LRI}{2} \tag{2}$$

3.5. Model evaluation

Model evaluation is a pivotal phase in assessing the BN model, particularly in understanding how extreme weather influences train delays [36]. This process examines the dependencies and relationships within the BN's structure to ensure that they accurately mirror the complexities of weather impacts on railway operations. The employed evaluation method thoroughly verifies that the model's output aligns well with real-world data on train delays during EWEs, maintaining logical consistency with established dynamics of weather and transportation systems. Moreover, the model's predictive capabilities are tested against scenarios of varying weather conditions to assess its effectiveness in real-time applications [32]. This extensive evaluation not only confirms that the BN effectively captures the interplay between EWEs and train delays but also demonstrates its robustness and utility for decision-making in rail network management. By simulating different weather scenarios, a deeper understanding of potential disruptions is gained, enabling more precise mitigation strategies. Thus, through comprehensive model evaluation, the BN is established not just as a theoretical construct but as a practical tool in minimising weather-related disruptions in train services.

3.5.1. Model correctness verification

In the quest for correctness verification within BN modelling, Li et al. [10] emphasise the vital commitment to two fundamental theorems during the reasoning process of sensitivity analysis. The initial theorem explains that any marginal adjustments, whether an increase or decrease in the prior probabilities of each test node, should consistently lead to corresponding adjustments in the posterior probability of the target node. This requirement ensures the integrity of the reasoning process, firmly establishing the sensitivity analysis within a resilient framework. The second theorem asserts that the authentic influence arising from the collective variations in the probabilities of the evidence must not be diminished when compared to the influence originating from a subset of the evidence. These theorems collectively establish a comprehensive foundation for executing sensitivity analysis, pivotal in the pursuit of model correctness verification in BN.

3.5.2. Predictive capability evaluation

The predictive capability stands as a pivotal aspect in the comprehensive evaluation of a model, specifically directed at measuring the proficiency of a BN in generating precise predictions for novel, unobserved data. This evaluation involves scrutinising the model's generalisability and its performance when applied to instances beyond the training dataset. To evaluate the predictive capabilities of the model, 155 delay records, randomly selected to represent 10 % of the dataset, are set aside for dedicated testing. This distinct subset serves as the testing dataset to scrutinise the model's efficacy in predicting outcomes.

3.5.3. Scenario analysis

In the domain of BN modelling, scenario analysis plays a crucial role in understanding how a system behaves under diverse hypothetical conditions. This analytical approach involves creating various scenarios, each illustrating a different realistic state of the system. For each scenario, specific values are assigned to the relevant variables within the BN structure. By then propagating these values through the network, the probabilities and dependencies intrinsic to the system are calculated. The outcome is a clear and probabilistic understanding of the likelihood of different events or the performance of the system under varying conditions [36]. This process aids decision-makers in comprehending the potential impact of uncertainties and in assessing the robustness of the model. Sensitivity analysis further contributes by highlighting the variables that exert the most influence on outcomes. Ultimately, scenario analysis serves as a valuable tool for decision support, enabling stakeholders to make informed choices based on a comprehensive exploration of the system's dynamics and responses to different scenarios. Its application is particularly pertinent in dealing with complex systems where uncertainties abound, providing a practical means to enhance risk assessment and decision-making processes.

4. Results and discussions

This section presents the findings derived from the BN model developed to analyse the risk of EWEs that cause train delays across the UK. Building upon the precisely cleaned dataset detailed in Section 3, the analysis focuses on the impacts of RIFs on train delays, revealing intricate dependencies and dynamic interactions within the UK railway system. Following comprehensive data collection and model calibration, the analysis elucidates the impact of various RIFs, such as severe weather conditions, on the probability of train delays. The results highlight the complex relationships and dependencies among the RIFs within the context of the UK railway system. By integrating these factors into a sophisticated probabilistic framework, the study quantifies not only the direct influences of individual weather events on train delays but also the compounded effects of multiple interacting RIFs. These insights are crucial for comprehending the dynamics of railway system disruptions and formulating effective strategies to mitigate the impacts of climate change on railway operations.

4.1. TAN modelling

Handling missing or incomplete data entries is essential for preparing the dataset for analysis. Each record is carefully reviewed to ensure it includes all necessary attributes for comprehensive evaluation. This ensures that every required data point for the model is complete and accurate. When key attributes crucial for analysis and prediction are found to be missing, these records are flagged. Due to the importance of complete data for the integrity of the analysis, records with missing critical attributes are removed from the dataset. This selective removal is crucial to prevent inaccuracies in the analysis and to maintain the dataset's quality. Through this careful management of missing data, the dataset remains reliable, supporting robust analyses and enabling precise assessments of the impacts of weather events on train delays. By maintaining high standards of data quality, the effectiveness of predictive models is ensured, and valid, actionable insights are derived from the study. This step is essential as it ensures the model is built on a complete and reliable data foundation, thus significantly enhancing its predictive accuracy and reliability. This step is essential as it ensures the model is built on a complete and reliable data foundation, thus significantly enhancing its predictive accuracy and reliability. The comprehensive examination extends beyond simply identifying incomplete records. It involves a systematic verification of data integrity and relevance, ensuring that each retained entry contributes positively to the model's objectives. This not only improves the model's accuracy but also enhances its efficiency by streamlining the dataset, reducing unnecessary complexity, and focusing on high-quality data inputs. Table 5 displays a sample of the data utilised in this modelling, illustrating how the dataset appears after the rigorous cleansing process.

The dataset presented in the table consists of 14 columns, each providing specific details regarding various delay incidents. This structured arrangement facilitates a comprehensive analysis of each delay, correlating with the detailed explanations provided previously in Table 3. Each column is tailored to capture distinct aspects of the delays, including the date, region of origin, planned action, and operational responses. This format allows for a systematic examination of patterns and causes behind the reported delays, supporting a robust analytical approach in delay management studies.

Using TAN to train the data from Section 3.1.2, a preliminary BN model for train delay analysis in the UK is developed and shown in Fig. 3, which is at the heart of the discussion. This visual helps explain the text by showing the actual links between the factors that contribute to train delays, as captured by the model. More importantly, the model discloses new links between the RIFs, which have yet to be found in existing literature. For example, it was found that a train's 'Planned Origin' is linked to the 'Day of the Week,' suggesting some places are more likely to have delays on certain days.

Further substantiation is provided through Fig. 3, which outlines the probabilities of all delay types as forecasted by the TAN model: 19.20 %, 18.70 %, 33.70 %, 17.00 %, and 11.40 %, respectively. These figures are then cross-referenced against the statistical outcomes obtained from the original dataset, which are as follows: 19.19 %, 19.06 %, 33.27 %, 17.03 %, and 11.39 %, respectively. The remarkable consistency between the predicted values and the actual data not only affirms the high fidelity of the model but also offers preliminary evidence supporting the model's initial accuracy. This close alignment across various metrics underscores the robustness of the predictive framework established by the TAN model, making it a reliable tool for forecasting delays.

4.2. Sensitivity analysis

4.2.1. Mutual information

Table 6 presents key metrics, including mutual information, entropy reduction percentage, and variance of beliefs. The analysis underscores the significant influence of 'months' on 'train delays', leading to a substantial mutual information value of 1.61161. Following closely are 'year' and 'origin location' with values of 0.58202 and 0.25634, respectively. These results highlight the varying impacts of different variables on the observed train delays.

Examining the mutual information value and its rate of change highlights a significant disparity, ranging from the initial factor, which is

Table 5
Dataset overview metrics.

No	Months	Years	Planned origin	Weekdays	Daytime	Planned destination	Application timetable	Train schedule	Traction type	Responsible manager	Incident reason	Attribution status	Event type	delays
1	Dec	2022	Anglia	Fri	Night	North & East	Y	(V)STP Base	D	East Midlands	10	Attribution Agreed	M	C
2	Jul	2022	North & East	Fri	Night	North & East	Y	(V)STP Base	D	North & East	12	Attribution Agreed	M	C
3	Mar	2023	West Coast South	Wed	Day	Scotland	Y	(V)STP Base	D	Scotland	5	Attribution Agreed	C	C
⋮	⋮													
1528	Oct	2022	Anglia	Fri	Night	Wales	Y	(V)STP Overlay	D	Western	5	Attribution Agreed	M	E
1529	Apr	2022	West Coast South	Wed	Day	Anglia	Y	(V)STP Overlay	D	West Coast South	1	Attribution Agreed	M	A
1530	Jun	2022	Anglia	Mon	Day	Anglia	Y	LTP	DME	Anglia	7	Attribution Agreed	M	E

'month', to the concluding factor, 'application timetable'. As illustrated in Table 6, months exhibit significantly higher differences compared to years. Subsequently, a moderate difference is observed between years and factors such as origin location and traction type. In contrast, the responsible operator, destination location, and event type display minor changes relative to each other. Notably, incident reasons occupy the 8th position among factors influencing train delays in the UK, considering these factors and the existing database.

4.2.2. Joint probability

The study uses joint probability distributions to assess how combinations of variables like weather, day of the week, and track conditions contribute to train delays. This analysis identifies critical risk factors and their impacts, enabling targeted strategies for railway operations. The probability of each state is indicated in Table 7.

Table 7 reveals for delays ranging from 60 to 70 min, the highest probability occurs in July, with December having the lowest probability. Similarly, for delays between 90 and 100 min, February holds the highest probability, while December has the lowest probability. For instance, it can identify whether certain weather conditions combined with a specific day of the week result in higher chances of delay, which can inform scheduling and resource allocation to mitigate these risks. In general, joint probability distributions provide a solid statistical foundation for predictive modelling and decision-making processes. They offer a nuanced understanding of complex systems where multiple factors interact, which is essential for optimising operations and improving service reliability in the railway industry. The term 'nuanced impacts' refers to the model's capability to accurately depict the varied consequences of different weather events on railway operations. This involves identifying how specific conditions like heavy snow, high winds, and extreme temperatures each uniquely influence railway operation.

4.2.3. True risk influence

Calculating TRI values involves applying the same analytical methodology to various RIFs and train delay scenarios. This process ensures a systematic assessment of how different RIFs contribute to train delays. The results, which detail the TRI values for each RIF concerning various types of delays, are shown in Table 8 below.

The TRI table serves as an assessment tool for evaluating the sensitivity of multiple variables within the BN Each node, about various delays, manifests distinct probabilities. While the TRI table provides an average overview, it does not specifically identify which node, within each delay category, exerts the most significant influence. The TRI table reflects the sophisticated nature of risk assessment, with 'Month' emerging as the leading factor, likely due to the harsher severe weather events experienced in the UK during December and January, which significantly impact operational safety and punctuality. The 'Incident Reason' also emerges as a pivotal factor, directly correlating to the delays and disruptions within the rail network. These insights underline the substantial influence of EWEs on railway operations, underscoring the importance of factoring seasonal variations and specific incident causes into risk mitigation strategies. This connection between weather-related incidents and operational delays accentuates the need for robust planning and response mechanisms within the rail industry to handle such climatic impacts more effectively. The planned origin follows, highlighting the importance of the journey's starting point. There's noticeable variability with the responsible operator and traction type, indicating these factors' impact changes significantly across different situations. The year and planned destination carry a moderate but consistent influence, implying that both temporal and locational aspects play stable roles in risk assessment.

SRIF, in contrast, assesses the relative importance of nodes when the target node is in a specific state. This helps clarify the impact of each factor within a particular scenario, offering a focused view on influence. These tools are indispensable for decision-makers, allowing them to identify and prioritise risk factors. These findings indicate that factors

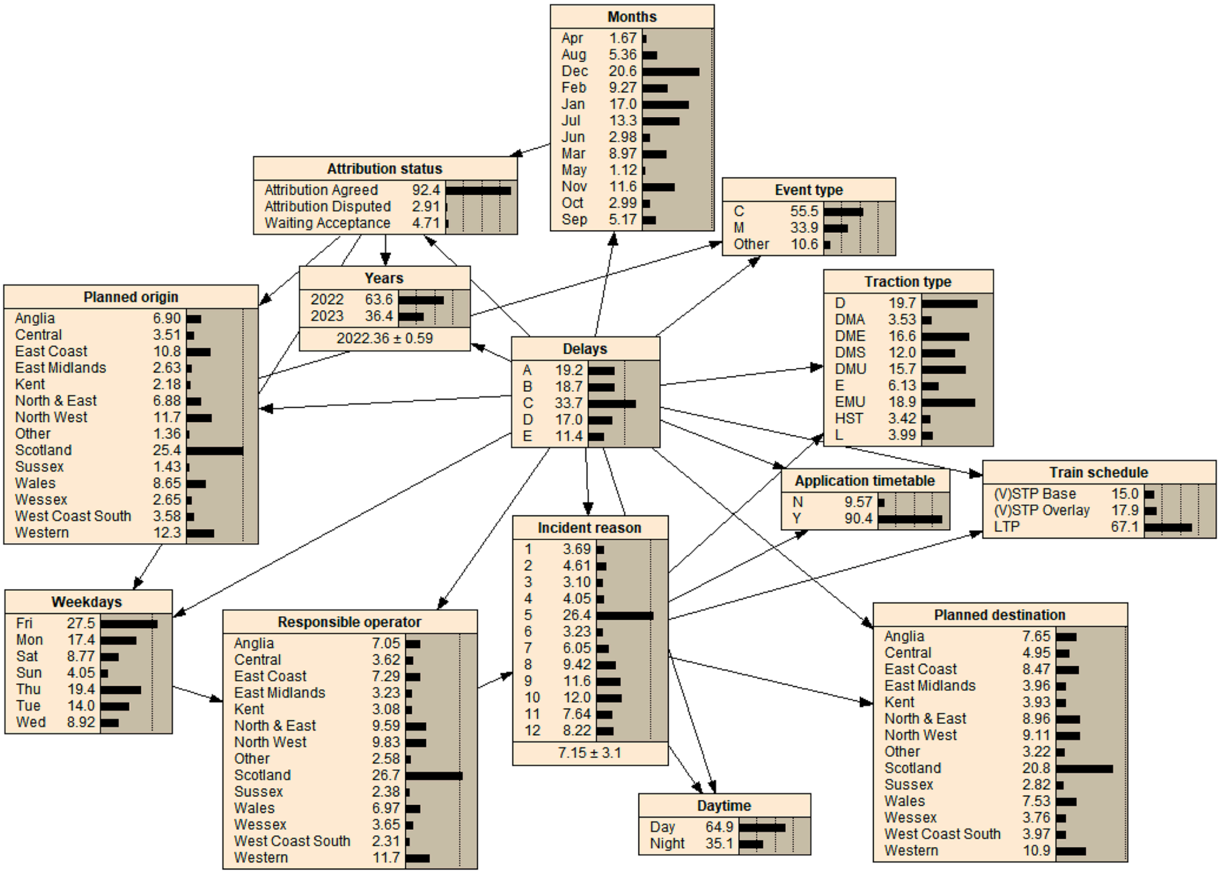

Fig. 3. The constructed TAN structure.

Table 6
Analysis of mutual information between the target node and RIFs.

Node	Mutual information	Reduction percentage	Variance of beliefs
Delays	2.23001	100	0.6037
Months	1.61161	72.3	0.3583
Years	0.58202	26.1	0.0253
Planned origin	0.25634	11.5	0.0258
Traction type	0.21709	9.73	0.0232
Responsible operator	0.17176	7.7	0.0162
Planned destination	0.13022	5.84	0.0123
Event type	0.10427	4.68	0.0052
Incident reason	0.07913	3.55	0.0062
Weekdays	0.04922	2.21	0.0035
Attribution status	0.01729	0.775	0.0022
Train schedule	0.01607	0.721	0.0008
Daytime	0.00589	0.264	0.0004
Application timetable	0.00083	0.0374	0.0001

such as ‘incident reason’ have a varied influence on train delays, underlining the need for a detailed approach to managing and reducing these delays. The TRI and SRIF tables facilitate this by delineating average influences and specific impact rankings, aiding in the development of targeted interventions. Table 9 is invaluable for identifying which factors are most crucial under particular circumstances.

The insights derived from the TRI and SRIF tables are highly valuable across different areas of the railway industry. Operational managers can leverage this data to allocate resources more effectively during high-risk periods, refine maintenance schedules to directly address specific causes of incidents, and develop tailored response strategies that enhance operational resilience. This strategic application of data ensures good deployment of resources to prevent and manage delays effectively. Strategic planners gain from understanding the variability in factor influence, especially the temporal shifts highlighted in ‘Month’, which aids in developing adaptive operational strategies that respond to both seasonal and situational dynamics. Moreover, policymakers and safety regulators benefit from a detailed analysis of contributing factors, which is crucial for creating policies that target the most impactful elements causing delays, thus improving the overall safety and efficiency of railway operations. Overall, the TRI and SRIF tables provide a systematic approach to examining how various factors influence delays and support strategic planning and operational adjustments to effectively manage and mitigate these delays. This data-driven approach is vital for enhancing the reliability and safety of rail transport, offering substantial benefits to operators and passengers alike and playing a pivotal role in advancing rail industry standards and practices.

4.3. Model evaluation

4.3.1. Model correctness verification

To ascertain the correctness of the BN model, the top nine RIFs associated with train delays, particularly focusing on those influenced by climate variables, were selected. These factors were subjected to incremental adjustments of ‘1 %’ in their prior probabilities to observe the resultant variations in the probability of ‘train delays’. This methodical adjustment, constrained by the model’s minimum probability change threshold of 1.11 %, was designed to ensure that each modification produced observable yet subtle impacts, thus allowing for the evaluation of the sensitivity and responsiveness of the model to small-scale changes in input variables. Table 10 illustrates the baseline probabilities for different scenarios of train delays and tracks how these probabilities

Table 7
The joint probability (100 %).

	A	B	C	D	E
Month					
January	0.41	0.41	42.3	56.5	0.40
February	0.76	0.76	0.77	**73.3**	24.4
March	0.80	0.79	0.81	0.79	**96.8**
April	83.4	4.16	4.24	4.15	4.06
May	75.1	6.25	6.36	6.22	6.09
June	90.7	2.32	2.37	2.31	2.26
July	**97.9**	0.52	**0.53**	0.52	0.51
August	13.0	83.1	1.32	1.29	1.27
September	1.32	**94.7**	1.34	1.31	1.28
October	2.28	90.9	2.32	2.26	2.22
November	0.60	50.2	48.1	0.59	0.58
December	**0.34**	**0.34**	**98.7**	**0.34**	**0.33**
Attribution status					
Attribution agreed	**17.6**	18.9	**34.6**	**17.5**	11.4
Attribution disputed	28.7	**19.9**	**21.3**	14.0	**16.1**
Waiting acceptance	**48.1**	**13.3**	22.2	**8.28**	**8.05**
Planned origin					
Anglia	**10.9**	**5.80**	**69.9**	1.71	11.7
Central	**35.5**	14.4	25.0	10.9	14.1
East coast	26.7	29.9	26.6	4.14	12.7
East midlands	23.9	28.1	24.3	9.62	14.2
Kent	22.8	15.6	38.9	8.56	14.2
North & East	26.8	10.6	46.2	4.60	11.8
North West	22.2	11.8	50.5	2.69	12.8
Scotland	11.4	14.4	18.3	45.7	10.3
Sussex	30.4	19.2	15.5	13.1	**21.8**
Wales	12.4	36.1	**11.3**	**29.5**	10.8
Wessex	21.3	**40.5**	26.8	4.53	**6.87**
West Coast South	13.8	13.1	52.5	3.32	17.4
Western	25.0	20.7	45.7	**1.50**	7.10
Other	22.4	15.4	37.4	8.99	15.8
Planned destination					
Anglia	14.5	**12.2**	**55.7**	7.71	9.90
Central	**30.4**	13.2	33.0	10.2	13.1
East coast	24.3	29.4	28.7	6.58	11.1
East midlands	22.3	18.5	34.3	12.6	12.3
Kent	23.2	18.4	31.9	11.7	14.8
North & East	27.0	14.7	40.0	8.04	10.2
North West	22.0	15.1	42.1	6.73	14.1
Scotland	**11.9**	13.8	23.0	41.0	10.3
Sussex	20.1	19.8	25.9	16.1	**18.1**
Wales	13.2	**30.3**	**16.3**	**28.1**	12.2
Wessex	19.9	30.2	25.5	13.1	11.1
West Coast South	15.8	15.5	39.6	12.7	16.6
Western	20.8	19.6	48.1	**4.93**	**6.53**
Other	20.2	25.9	25.8	15.2	12.9
Traction type					
D	9.89	**12.0**	**54.3**	6.83	**16.9**
DMA	20.4	19.9	25.4	18.0	16.3
DME	**8.34**	13.7	19.5	**54.1**	**4.38**
DMS	18.9	**28.7**	**18.5**	21.4	12.4
DMU	**33.8**	10.8	43.7	4.85	6.95
E	27.9	21.4	22.9	12.2	15.6
EMU	23.3	27.4	35.3	**3.56**	10.5
HST	21.0	22.2	22.8	17.2	16.8
L	19.4	22.7	25.5	16.0	16.3
Incident reason					
1	18.6	**27.6**	26.5	12.2	15.1
2	19.1	16.6	29.0	13.7	**21.6**
3	22.8	19.8	27.4	14.5	15.5
4	25.1	24.3	24.2	11.8	14.6
5	**11.9**	18.6	38.2	22.2	9.07
6	25.4	19.0	26.4	13.9	15.3
7	14.0	22.7	22.7	22.5	18.1
8	18.8	16.6	45.5	9.09	10.0
9	21.4	16.1	**50.2**	6.34	**6.02**
10	25.5	25.6	**17.5**	19.4	12.0
11	19.2	**10.7**	23.1	**34.8**	12.1
12	**28.8**	13.0	39.7	**8.91**	9.67
Year					
2022	29.5	28.4	40.9	0.68	0.60
2023	0.78	1.10	20.7	46.5	30.9
Responsible operator					
Anglia	12.7	**8.19**	**61.0**	6.53	11.6
Central	**11.3**	19.3	33.3	14.3	**21.8**
East coast	**33.5**	30.1	20.5	5.66	10.3
East midlands	22.9	24.7	27.5	11.5	13.4
Kent	22.5	19.3	34.9	10.3	12.9
North & East	26.1	13.0	41.4	6.76	12.8
North West	19.7	11.4	53.7	4.40	10.8
Scotland	11.4	15.3	25.1	**37.0**	11.1
Sussex	26.8	19.4	22.0	15.1	16.6
Wales	11.4	33.4	**13.0**	31.7	10.6
Wessex	15.9	**47.2**	20.2	8.66	7.97
West Coast South	19.9	17.6	32.2	13.8	16.5
Western	30.8	16.9	42.1	**3.52**	**6.65**
Other	19.5	17.4	35.9	12.3	14.9
Event type					
C	16.3	**15.6**	36.3	25.6	6.26
M	**27.6**	20.9	**24.8**	6.00	20.7
Other	**8.23**	**27.9**	**48.5**	6.53	8.87
Train schedule type					
(V) STP Base	19.0	16.2	40.1	10.8	13.8
(V) STP Overlay	17.3	17.9	34.9	12.5	17.4
LTP	19.8	19.4	31.9	19.7	9.21
Applicable timetable flag					
Yes	19.1	18.5	34.3	17.0	11.1
No	20.2	20.4	28.5	16.6	14.3
Daytime					
Day	18.5	19.8	31.9	18.9	11.0
night	20.7	16.5	37.0	13.6	12.2
Weekdays					
Monday	24.1	22.6	32.6	10.8	9.98
Tuesday	21.7	13.0	**46.7**	8.49	10.1
Wednesday	**28.1**	**12.9**	29.7	15.7	13.7
Thursday	**12.1**	18.7	37.2	17.9	14.0
Friday	17.9	19.8	26.3	**24.7**	11.3
Saturday	19.4	14.6	38.2	22.1	**5.69**
Sunday	13.6	**35.4**	**26.0**	**7.72**	**17.4**

Table 8
TRI of SRIF for different delays.

	A	B	C	D	E	Average
Month	48.78	47.18	49.08	36.48	48.23	45.95
Planned origin	12.3	17.35	29.3	14	7.5	16.09
Responsible operator	11.1	19.50	24	16.74	7.57	15.78
Year	14.36	13.65	10.1	22.91	15.15	15.23
Traction type	12.73	8.35	17.9	25.27	6.26	14.10
Planned destination	9.25	9.05	19.7	11.58	5.78	11.07
incident reason	8.45	8.45	16.35	12.94	7.79	10.79
Event type	9.68	6.15	11.58	9.8	7.22	8.88
Weekdays	8	11.25	10.35	8.49	5.85	8.78
Attribution status	15.25	3.3	6.65	4.61	4.02	6.76
Train schedule	1.25	1.6	4.1	4.45	4.09	3.09
Daytime	1.1	1.65	2.55	2.65	0.6	1.71
Applicable timetable flag	0.55	0.95	1.2	0.2	1.6	0.9

evolve with systematic adjustments to the RIFs' probabilities. Each subsequent column beyond the first reveals the cumulative effect of these adjustments, highlighting the model's capability to respond dynamically to changes in each influencing factor. This aspect of the model is crucial, demonstrating its potential utility in predicting the effects of incremental climatic changes on 'train delays'.

The initial probabilities of various types of train delays, as presented in the second column of Table 10, are based on data extracted from the dataset. The subsequent columns trace how these probabilities evolve in response to incremental changes in the prior probabilities of key RIFs. Each adjustment is independently calculated to reflect the model's sensitivity to individual RIF adjustments, illustrating the dynamic nature of train delays in changing climate conditions. The results showing no abrupt and unexpected probability changes, are in line with the

Table 9
The importance rankings of SRIF for delays.

	A	B	C	D	E
Months	1	1	1	1	1
Years	3	4	9	3	2
Planned origin	5	3	2	7	4
Traction type	4	8	5	2	7
Responsible operator	6	2	3	4	5
Planned destination	9	6	4	8	9
Event type	7	9	7	9	6
incident reason	8	7	6	6	3
Weekdays	10	5	8	10	8
Attribution status	2	10	10	5	11
Train schedule	11	12	11	11	10
Daytime	12	11	12	12	13
Applicable timetable flag	13	13	13	13	12

impact of each variable on the delay effects. This independent assessment of cumulative probabilities underlines the robustness of the BN model in capturing and predicting the subtle impacts of climatic variations on railway operations. Overall, the detailed evaluation of the BN model through this verification process not only confirms its correctness but also emphasises its critical role in understanding and managing the complexities of train delays under varying climatic conditions.

4.3.2. Predictive capability evaluation

The predictive capability of the model is evaluated using a comprehensive confusion matrix, as detailed in Table 11. In evaluating the predictive capability of the model, the dataset was split into training and testing subsets using a 90:10 ratio. This ratio is crucial for balancing the need for sufficient training data to capture the complexities of railway operations and enough testing data to robustly validate the model's predictions. Specifically, 90 % of the data was used for training, exposing the model to a diverse range of data patterns, while the remaining 10 % was reserved for testing to assess performance and generalisability [19]. Optimal data splitting ratios can vary, but the 90:10 split used in this evaluation is well-supported in practice and aligns with the principle that larger training sets are beneficial for complex models. This approach ensures the model's robustness and effectiveness in practical applications, confirming its suitability for deployment in operational settings [45,46].

Predictive accuracy is exhibited by the model, as evidenced by an overall accuracy rate of 93.99 %, calculated from the matrix derived from the test data. As shown in Table 11, the model's accuracy for state A, representing train delays between 60–70 min, is exceptionally high at 96.67 %. This accuracy for states B (70–80 min) and C (80–90 min), maintains strong rates of 91.43 % and 91.11 %, respectively. Additionally, in the latter states, D (90–100 min) and E (over 100 min), the accuracy rates are notably high as well, at 96.30 % and 94.44 %, respectively. All the accuracy rates are higher than the recommended value in the literature for model validation [46].

The accuracy rates detailed above are indicative of the model's strength in handling real-world data and its efficiency in generalising from the training data to unseen scenarios encountered in the test data. This approach not only validates the predictive power of the model but also ensures that it can be reliably used for practical purposes such as planning and operational adjustments in railway systems facing various delay durations.

4.3.3. Scenario analysis

Scenario analysis provides a robust framework for assessing the impacts of extreme weather on train delays, concentrating on the complex interrelationships among various risk factors. The analysis defines two primary scenarios to evaluate the railway network's resilience and preparedness in adverse conditions.

(1) Severe flood.

The chosen scenario developed for this study methodically examines two discrete variables: a severe flood and the month of December. These components were independently selected to clarify their unique contributions to the overall risk profile. This methodological choice is supported by the predictive analytics of the model, which highlights these variables, severe flood and December, as exhibiting the most significant risk within their respective categories. In this setup, the 'severe flood' and 'December' are attributed to a probability of 100 % at the state that maximises joint probability with delay durations. Analysis of this scenario reveals a distinct pattern: despite a general reduction in delays, there is a significant escalation in the incidence of delays ranging from 80 to 90 min, increasing from 33.7 % to 98.9 %. Delays of such length are categorised as severe and frequently precipitate train cancellations. This observation suggests that train delays, particularly significant in scenarios involving severe floods and often coinciding with December, are of such significance, often leading to cancellations.

Severe floods and the month of December are integral elements of the scenario, with a heightened risk of extended delays that can lead to significant operational disruptions and potential infrastructure damage. This complexity intensifies the challenges the

Table 11
Confusion matrix of predicted results.

		Actual					Actual total	Accuracy rate
		A	B	C	D	E		
Predicted	A	29	1	0	0	0	**30**	96.67 %
	B	1	32	2	0	0	**35**	91.43 %
	C	0	1	41	3	0	**45**	91.11 %
	D	0	0	0	26	1	**27**	96.30 %
	E	1	0	0	0	17	**18**	94.44 %
	Total	**31**	**34**	**43**	**29**	**18**	**155**	93.99 %

Table 10
The output of minor changes in SRIFs.

Weekdays	–	+1 %	+1 %	+1 %	+1 %	+1 %	+1 %	+1 %	+1 %	+1 %
Incident reason	–	–	+1 %	+1 %	+1 %	+1 %	+1 %	+1 %	+1 %	+1 %
Event type	–	–	–	+1 %	+1 %	+1 %	+1 %	+1 %	+1 %	+1 %
Planned destination	–	–	–	–	+1 %	+1 %	+1 %	+1 %	+1 %	+1 %
Responsible operator	–	–	–	–	–	+1 %	+1 %	+1 %	+1 %	+1 %
Traction type	–	–	–	–	–	–	+1 %	+1 %	+1 %	+1 %
Planned origin	–	–	–	–	–	–	–	+1 %	+1 %	+1 %
Years	–	–	–	–	–	–	–	–	+1 %	+1 %
Months	–	–	–	–	–	–	–	–	–	+1 %
A	19.2	19.4	19.5	19.7	20.7	20.7	20.9	21.2	21.7	22.7
B	18.7	19	19.1	19.3	19.5	19.9	20.1	20.5	21	22.6
C	33.7	33.9	34.2	34.6	35	35.6	35.9	36.5	36.9	37.8
D	17	17.2	17.5	17.7	18	20	20.6	23	23.8	24.6
E	11.4	11.5	11.7	11.8	12	12.2	12.3	12.5	13	14

railway network faces during EWEs. Such conditions underscore the critical need for targeted strategies to mitigate the impacts of these events, particularly to safeguard operational efficiency and infrastructure integrity. It is noteworthy that during occurrences of severe floods, particularly in December, the probability of delays between 80 and 90 min rises sharply to 98.9 %, as shown in Fig. 4.

(2) The most likely scenario for specific train delays.

The second scenario analysis evaluates the cumulative effects of various RIFs, focusing on scenarios that pose the highest risk of train delays. The model highlights Scotland as a significant risk area, both as a point of origin and a destination. Consequently, Scotland is selected as the 'planned origin' and 'planned destination' with probabilities fixed at 100 % to investigate the effects of these high-risk scenarios. To add depth to the analysis, geographical factors are combined with operational management considerations. Scotland is chosen as the operator responsible, with the selection probability also set at 100 %. This choice illustrates the interaction between geographical and operational elements, as well as EWEs, with flooding playing a crucial role in this complex mix. Further analysis reveals a significant correlation between elevated risk settings in Scotland, designated as the origin, destination, and responsible operator and the incidence of floods. As shown in Fig. 5, this correlation indicates that when the probability of train routes involving Scotland increases under flood conditions, the likelihood of encountering 'D' category delays within the 90–100-minute range surges dramatically from 17 % to 85.7 %. This substantial increase significantly amplifies the risk of extended delays.

Such an increase underscores an exceptionally high risk of prolonged delays, often culminating in service cancellations, particularly under the severe weather conditions prevalent in Scotland. Additionally, the results of this scenario suggest a direct correlation between geographical and meteorological factors, emphasising the interaction between these elements in intensifying delay probabilities. This comprehensive understanding reinforces the need for strategic planning and risk management tailored to address the unique challenges posed by flooding in high-risk regions such as Scotland.

(3) December train delays: a weather impact scenario analysis.

In the third scenario analysis (Fig. 6), the probability of train delays in December, known for the highest risk, was increased by 20 %, from 20.6 % to 24.7 %, based on evidence that December is prone to extreme weather events (EWEs) affecting UK train operations. This change showed that while delays in categories A, B, D, and E decreased, delays in Category C (80–90 min) increased from 33.7 % to 44.5 %. This indicates that December disruptions, often due to EWEs, typically last 80–90 min. This analysis not only highlights the specific impact of December's harsh weather conditions on train delays but also reinforces the necessity for tailored operational strategies during this high-risk period.

Table 12 shows the probability of five distinct train delays over a yearly cycle, enumerated from January (1) to December (12). For instance, Category A peaks in February at 93.4 % but drops to 0.036 % in March, possibly due to effective management of February's challenges. Category B delays jump from 0.14 % in July to 83.1 % in August, likely due to summer operational demands. Category C delays peak at 98.7 % in December, suggesting cumulative factors like bad weather and holiday travel. Category D shows high probabilities in March (96.1 %) and July (97.8 %), with a drop in April (23.4 %), indicating periodic adjustments. These fluctuations could indicate periodic operational

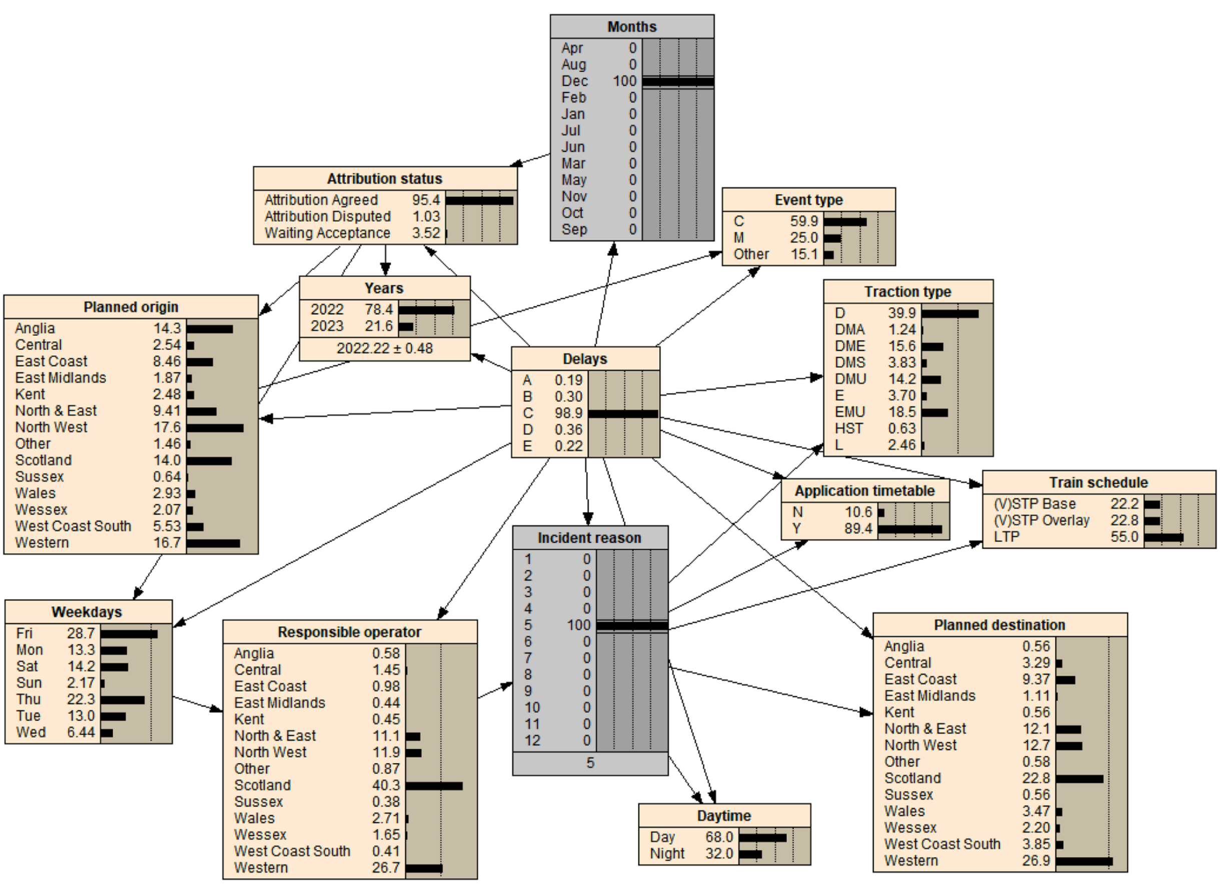

Fig. 4. Scenario one: severe flood.

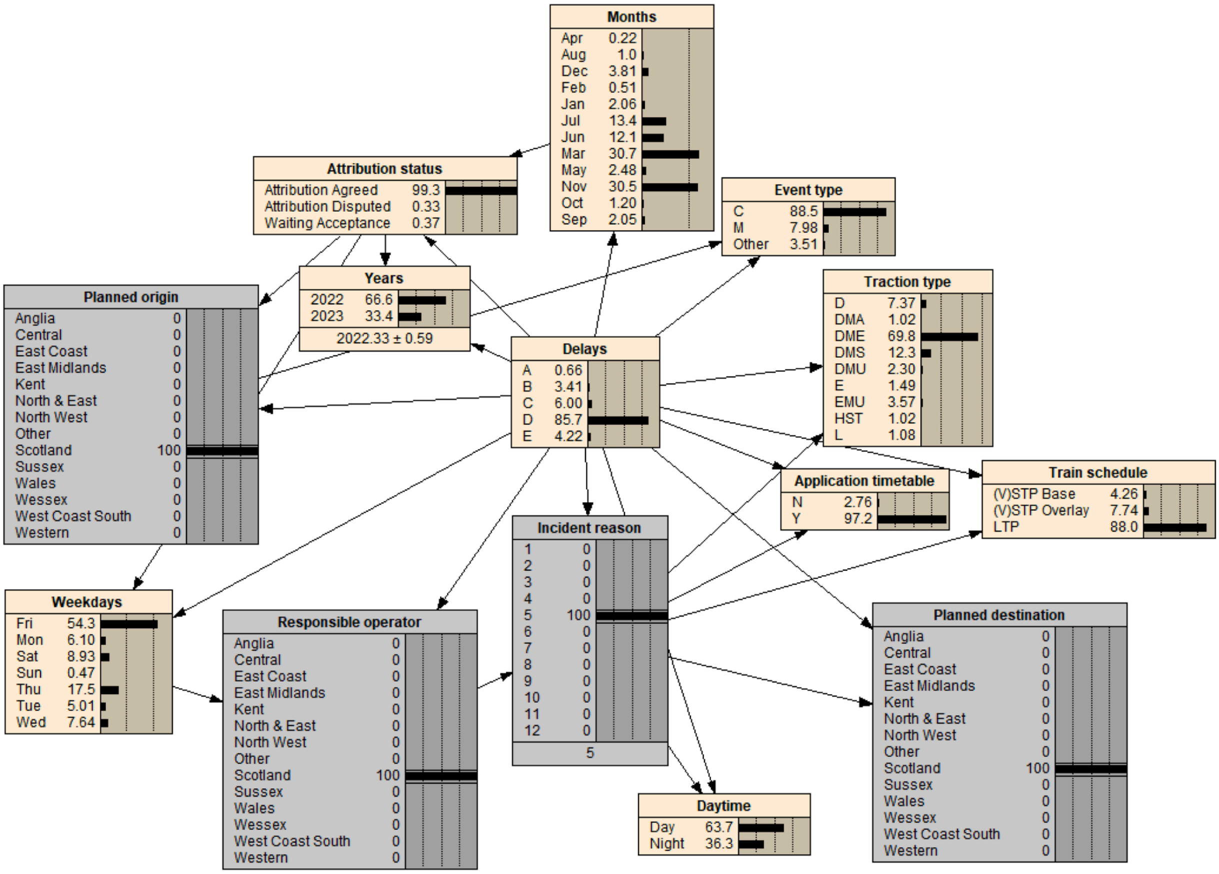

Fig. 5. Scenario two: planned origin and planned destination.

adjustments or maintenance schedules that either exacerbate or alleviate delays. Category E peaks in September (94.6 %) and October (90.7 %), highlighting late-year challenges. For instance, this suggests that these months are particularly prone to conditions that severely impact rail operations, potentially including adverse weather and operational overloads.

4.3.4. *Consequence analysis using utility node*

This section elaborates on the impact of scenario-based adjustments within the BN model, focusing on how these adjustments affect risk assessment outcomes. The primary objective of this work is to quantify and analyse the potential risks associated with EWEs and regional factors affecting railway operations. By integrating decision and utility nodes into the BN, the model predicts the likelihood of delays and evaluates the severity of their consequences, providing a comprehensive risk profile. The model currently outputs a risk value of 0.56528 (see Fig. 7), which reflects an integrated assessment of various operational parameters without any scenario adjustments. This value indicates a moderate to significant risk level, serving as a crucial metric for operational management and strategic planning in railway operations.

(1) Scenario 1: Assessing the impact of increased flooding probability

In the first scenario, the model adjusted the probability associated with flooding (labelled as incident reason 5) to 100 %, effectively simulating a scenario where flooding is certain. This is a critical test because flooding significantly disrupts railway services by damaging infrastructure and slowing down operations. Within the BN, the utility node plays a crucial role by assigning specific utility values to different categories of train delays, ranging from Category A (least severe) to Category E (most severe). These utility values are scaled from 0.2 to 1, with 0.2 indicating no impact (Category A) and 1 representing the highest impact (Category E), which involves extensive delays and disruptions. Following this recalibration, the decision node integrates these utility values to compute an overall risk value. For this flooding scenario, the risk value was calculated to be 0.595. Fig. 8 quantitatively reflects an elevated risk level, indicating a significant potential for operational disruption due to severe weather conditions. Essentially, the decision node's output of 0.565 underscores the heightened operational risk under extreme flooding conditions, demonstrating the model's capability to predict and quantify the impacts of specific adverse events on railway operations.

(2) Scenario 2: geographical risk analysis with a focus on Scotland

The second scenario involved altering the origin and destination nodes to focus solely on Scotland. This adjustment was crucial for understanding the regional specificity of risk, as Scotland's topography and climate pose unique challenges to railway operations. Upon setting both the origin and destination to Scotland, the BN recalculated the associated risk metrics, reflecting the heightened regional risks. The decision node adjusted the risk value to 0.71 (see Fig. 9), illustrating how local conditions influence overall risk levels.

The integration of scenario analysis within the BN framework significantly enhances the ability to perform detailed and responsive risk assessments. This approach not only aligns with advanced risk management practices but also provides a comprehensive method for assessing and mitigating risks in railway operations. The detailed analysis of each scenario helps in understanding the specific contributions of various risk factors, thereby enabling targeted interventions based on empirical data and sophisticated modelling techniques.

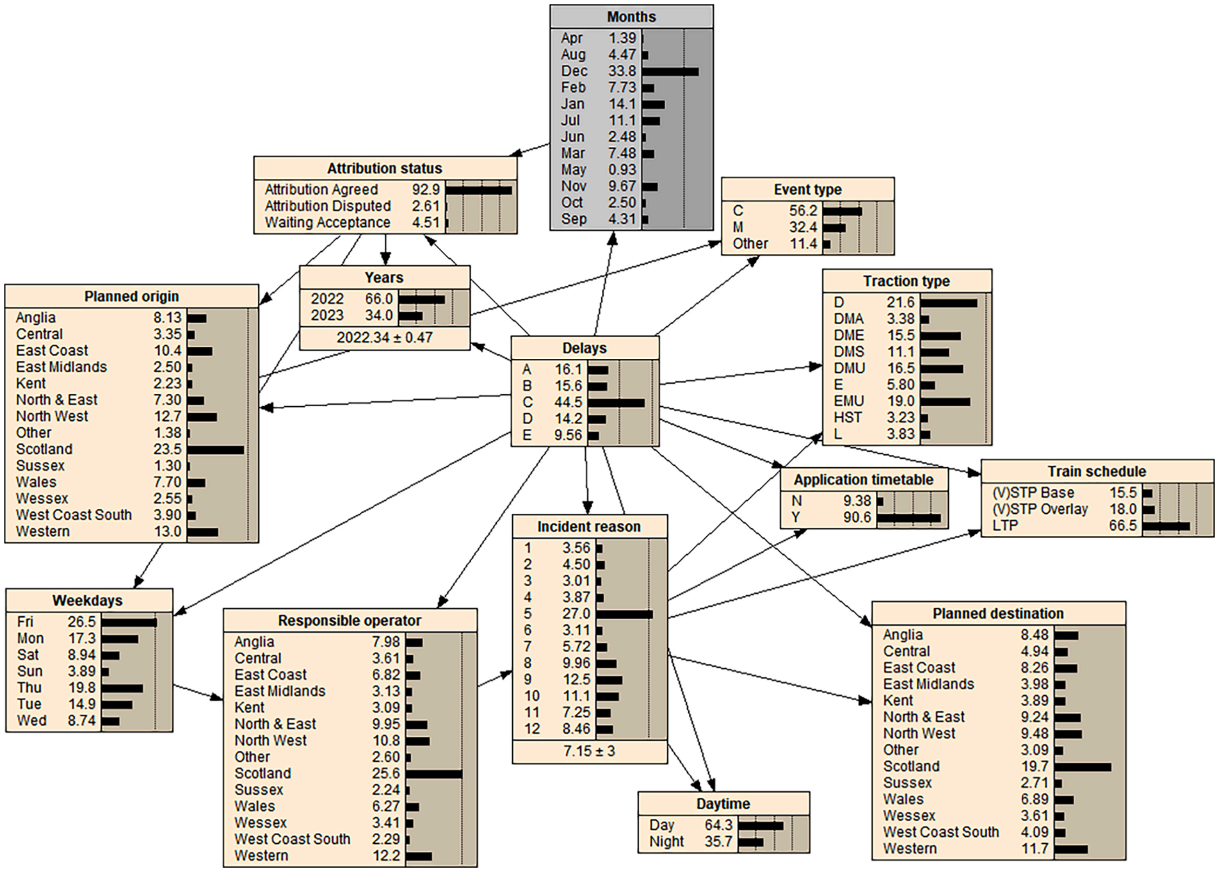

Fig. 6. Scenario 3: December train delays: a weather impact scenario analysis.

Table 12
Seasonal variations in train delay risks across 5 duration categories.

	Months												Average
Delays	1	2	3	4	5	6	7	8	9	10	11	12	
A	36.1	93.4	0.036	68.0	0.44	0.092	0.068	13	1.35	2.33	0.60	0.34	17.98
B	34.7	0.58	0.056	2.82	0.69	0.14	26.4	83.1	1.35	2.33	0.60	0.34	12.76
C	26.2	0.41	1.96	2.00	3.41	0.10	1.16	1.32	1.37	2.37	41.6	98.7	15.05
D	2.64	4.80	96.1	23.4	94.5	97.8	68.5	1.29	1.34	2.32	48.4	0.34	36.79
E	0.43	0.78	1.87	3.80	0.92	1.85	3.85	1.27	94.6	90.7	8.78	0.33	17.43

4.3.5. Seasonal and regional variability in train delays

Annual averages show Category D (90–100 min) has the highest delay probability (36.79 %), indicating severe weather impacts. Category B (70–80 min) has the lowest (12.76 %), suggesting less severe disruptions. Understanding high-risk months helps rail operators implement preventive measures, improving service reliability. Rail operators can implement preventive measures and allocate resources more efficiently during these high-risk periods, thereby enhancing service reliability and improving passenger communication. Such strategic insights enable operators to anticipate potential disruptions more effectively, ensuring a more robust and responsive rail system.

Table 13 outlines the maximum and minimum temperatures recorded across the UK, segmented by month and sourced from meteorological reports by the Met Office. A deeper analysis reveals patterns in temperature extremes and their geographical distribution across England, Scotland, and Wales, providing insight into regional climatic conditions. Scotland consistently registers the lowest temperatures throughout the year, with Inverness-shire and Aberdeenshire frequently appearing as the coldest regions. This is particularly evident in the winter months, with December showcasing Aberdeenshire plunging to a chilling $-17.3\,^{\circ}$C. Such extreme cold is notable in the context of the UK's climatic variations and is predominantly concentrated in the northernmost regions of Scotland. Consequently, these measurements substantiate the high accuracy of our model. In contrast, England records the highest temperatures, with a notable peak in Lincolnshire reaching 40.3 $^{\circ}$C in July. Southern and Eastern England tend to experience these warmer extremes, a pattern that aligns with these regions' more continental climate, which allows for hotter conditions during the summer.

This geographical disparity in weather extremes between Scotland and England, particularly Scotland's significantly lower temperatures, can be directly linked to operational challenges, such as those affecting railway services. Extreme cold can lead to mechanical failures, signal problems, and track issues, which are likely contributors to the higher frequency and severity of train delays observed in Scotland. The recurrent low temperatures in Scotland, as highlighted in the table, justify why this region experiences the most substantial weather-related disruptions to train services. Therefore, it is evident that Scotland's harsher climate, specifically its colder extremes, significantly contributes to the higher incidence of train delays compared to other regions. This insight underscores the necessity for robust weather resilience strategies within Scottish rail infrastructure to mitigate the impact of severe weather conditions on train reliability and safety.

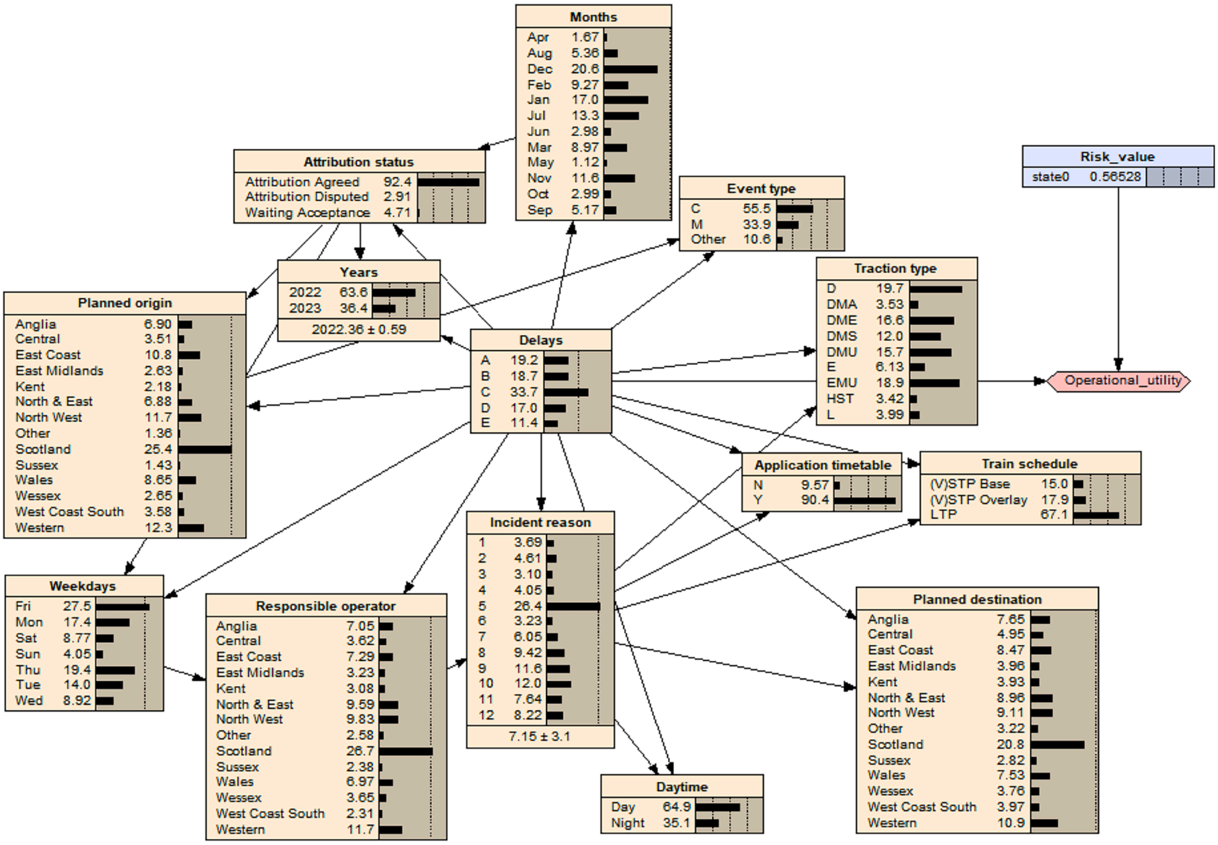

Fig. 7. Baseline risk assessment in railway operations.

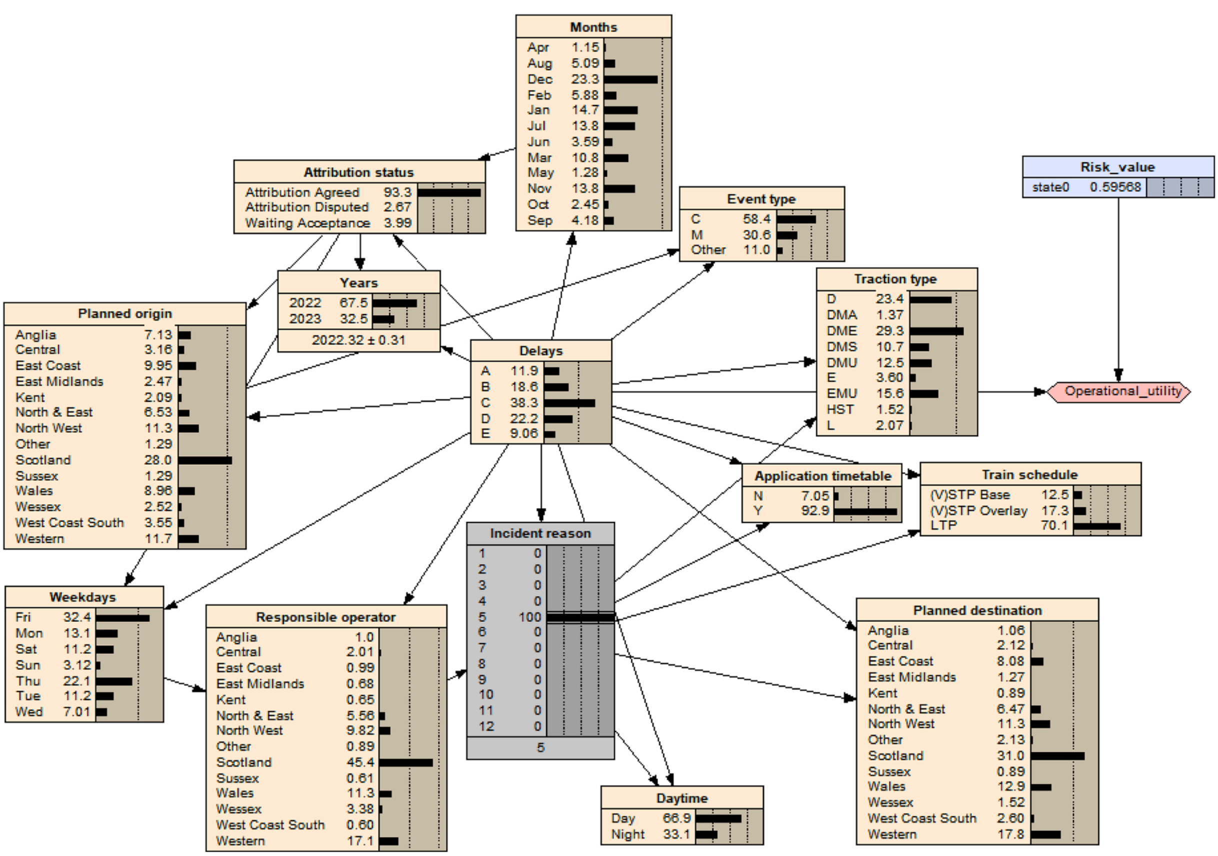

Fig. 8. Bayesian network risk assessment with elevated flooding probability scenario.

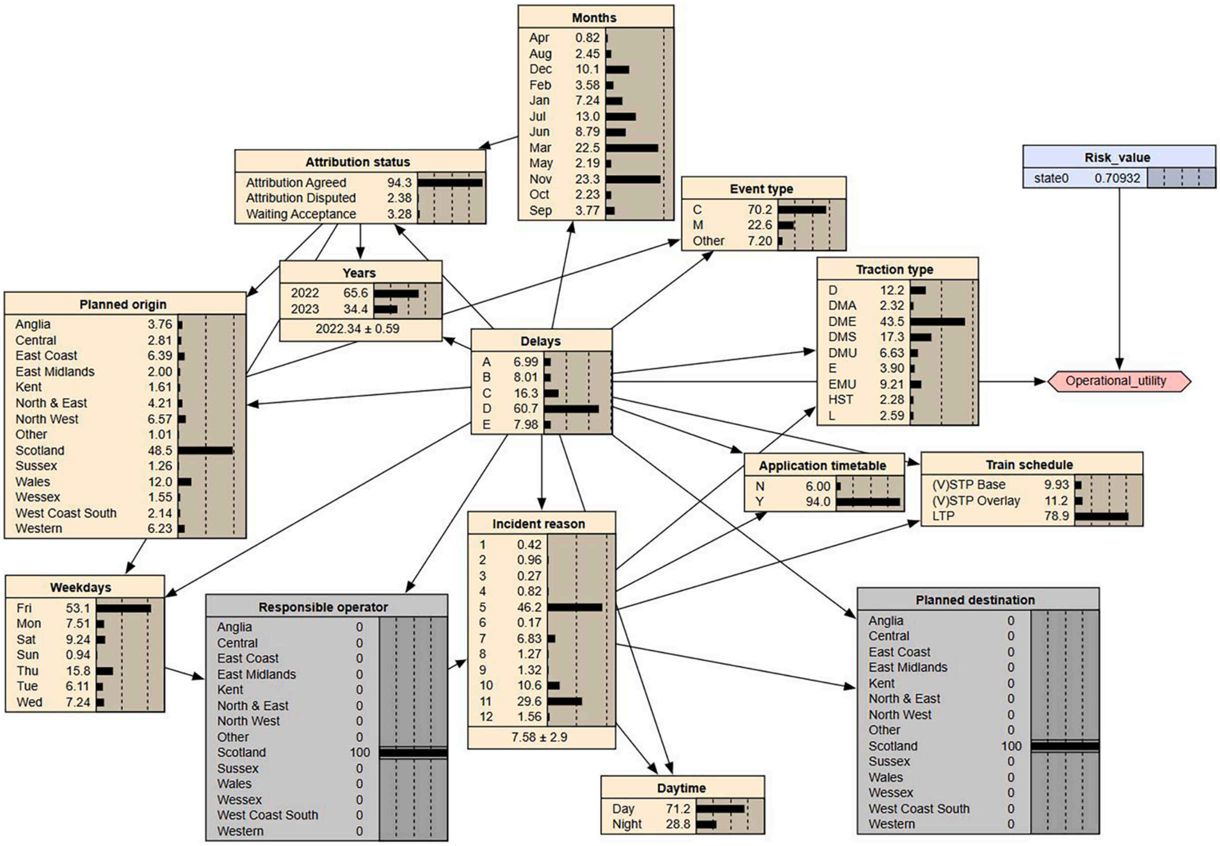

Fig. 9. Bayesian network risk assessment with a geographic focus on Scotland.

Table 13
Monthly temperature extremes across UK regions: highest and lowest recorded by Met office.

Months	Region/ Max temperature	Region/ Min temperature
Jan	Aberdeenshire, Scotland/ 15.8 °C	Inverness-shire, Scotland/ −10.4 °C
Feb	Hereford & Worcester, England/ 17.2 °C	Inverness-shire, Scotland/ −8.5 °C
March	Suffolk, England/ 17.8 °C	Sutherland, Scotland/ −16.0 °C
Apr	London, England/ 23.4 °C	Inverness-shire, Scotland/ −8.0 °C
May	London, England/ 27.5 °C	Sutherland, Scotland/ −1.7 °C
June	London, England/ 32.7 °C	Sutherland, Scotland/ −1.5 °C
July	Lincolnshire, England/ 40.3 °C	Perthshire, Scotland/ 2.3 °C
Aug	Surrey, England/ 34.9 °C	Inverness-shire, Scotland/ 0.3 °C
Sep	Suffolk, England/ 27.7 °C	Cumbria, England/ −1.7 °C
Oct	London, England/ 22.9 °C	Aberdeenshire, Scotland/ −3.8 °C
Nov	Gwynedd, Wales/ 21.2 °C	Inverness-shire, Scotland/ −6.0 °C
Dec	Clwyd, Wales/ 15.9 °C	Aberdeenshire, Scotland/ −17.3 °C

Table 14
Monthly trends in train delays by origin, destination, and severity.

Months	Origin	Destination	Delays
January	Western (17.5)	Scotland (14.0)	A (44.8)
February	Scotland (16.6)	Scotland (13.2)	A (97.0)
March	Scotland (50.8)	Scotland (37.8)	D (64.1)
April	Scotland (15.9)	Scotland (14.7)	A (83.4)
May	Scotland (34.9)	Scotland (32)	D (49.7)
June	Scotland (57.3)	Scotland (43.3)	D (79.2)
July	Scotland (28.0)	Scotland (21.3)	B (69.9)
August	Scotland (19.0)	Scotland (15.5)	B (83.1)
September	Scotland (23.0)	Scotland (19.0)	E (94.6)
October	Scotland (27.6)	Scotland (19.2)	E (90.7)
November	Scotland (41.9)	Scotland (32.0)	D (48.4)
December	North west (17.6)	Western (15.5)	C (98.7)

Table 14 offers an insightful analysis of train delays throughout the UK, documenting delay severity and identifying the most affected routes each month. In January, trains originating from Western regions report significant delays, with durations between 60 and 70 min (Category A). Similarly, any trains arriving in Scotland this month face comparable delays, underlining challenges that are not restricted to specific routes but potentially widespread across different segments. February sees an escalation in delay durations with a striking 97.0 % probability of delays remaining within the 60–70-minute range (Category A), suggesting ongoing and perhaps intensifying operational challenges. As spring approaches in March, the severity peaks with delays of 90–100 min (Category D), indicating critical disruptions, which slightly decrease in April, yet remain significant.

The pattern of increasing severity continues into the summer, with June particularly notable for prolonged delays (Category D), which are influenced by a seasonal increase in travel demand and high temperature. Conversely, July and August show a shift to slightly shorter delays (Category B), though the likelihood remains high, suggesting persistent challenges during peak tourist season and temperature. The most severe disruptions occur in the autumn, particularly in September and October, where delays extend beyond 100 min (Category E), likely exacerbated by adverse weather such as heavy precipitation.

4.4. Findings and implications

This research undertakes a comprehensive analysis of all risk factors contributing to train delays, precisely evaluating each factor's impact. Among these, delays resulting from EWEs are identified as particularly high-risk. Consequently, these weather-related delays are prioritised for focused study and detailed examination, ensuring a thorough understanding of their significant impact on railway operations. The comprehensive analysis of the BN model identified 13 key factors influencing train delays, with a significant emphasis on temporal elements. December emerged as the month with the highest probability of delays (20.6 %), followed closely by January and July, indicating a correlation between adverse weather conditions and heightened transportation demand. The data predominantly consists of entries from 2022, accounting for 64.4 % of the total, highlighting the relevance of this specific year within the study period (April 2022 to March 2023).

Geographically, trains originating from Scotland face the highest risk of delays, affecting both their starting and ending points. This spatial insight is crucial for developing targeted strategies to mitigate delays in specific regions. Among the causes of delays, extreme weather events, particularly floods (identified as incident reason number 5), are the predominant factors, underscoring the vulnerability of the rail network to such conditions. The study emphasises delays exceeding 60 min, which has significant implications for passenger compensation and operational challenges. The necessity for robust, weather-responsive strategies within rail systems is validated by the model's alignment with actual weather data, confirming the importance of integrating these strategies.

The study also revealed that environmental factors make diesel locomotives and multiple units more susceptible to delays. A significant clustering of delays between 80–90 min provides further insights for operational interventions. Notably, Fridays are identified as peak risk periods for delays, suggesting the need for refined scheduling strategies. Finally, the correlation between Scotland's geography and meteorological conditions, particularly flooding, is evident. This geographic and meteorological link significantly influences the frequency and severity of train delays, particularly in Scotland. Based on the previous findings, several valuable implications can be identified. The integration of the data-driven BN method into transportation risk assessment represents a significant advancement in managing train delays. This study, leveraging a comprehensive Network Rail dataset, highlights the importance of addressing delays over 60 min due to their legislative and economic impacts.

An interactive approach is essential, particularly during high-risk months. The model's alignment with actual weather data underscores the need for robust, weather-responsive strategies in rail systems. Targeted interventions, such as resource allocation, staff training, and infrastructure fortification, are crucial for improving service reliability and passenger satisfaction. Introducing novel RIFs enhances operational risk assessment, emphasising the impact of weather-related incidents like flooding. Recommendations include evaluating fleet compositions and refining schedules, particularly on high-risk days like Fridays. Investments in weather-resistant materials and early warning technologies are vital for bolstering infrastructure resilience.

This research underscores the adaptability of this BN model for its application in road transportation systems. The strength of this methodology lies in its data-driven approach and thorough evaluation of risk factors, rendering it equally applicable to road networks. By gathering and assimilating data on road closures and disruptions caused by EWEs, such as heavy precipitation, floods, and snow, similar to the method employed for railway data, the BN model can proficiently forecast and manage risks associated with road transportation. The model's flexibility and comprehensive analytical framework establish it as an indispensable tool for boosting resilience across various modes of transportation. The BN model's predictive capacity offers a strategic advantage, enabling anticipation and prevention of disruptions, thereby driving economic gains and policy development. Identifying key delay factors allows for strategic interventions to enhance punctuality and safety, improving overall operational efficiency and passenger experiences. This data-driven approach promises significant economic benefits and policy advancements for the rail industry.

5. Conclusions

This study successfully applied a data-driven BN methodology to construct a robust model that can quantify and analyse the complex risks associated with train delays across the UK. Utilising an extensive dataset from Network Rail for the year 2022–2023, the research performed a detailed data-cleaning process to identify and refine 13 RIFs for in-depth analysis. The BN-based risk model facilitated sensitivity analyses, model evaluations, and diverse scenario simulations, revealing key factors influencing train delays. The results highlighted the intricate interactions between different nodes and the impact of various states on the target node, thereby enhancing strategies to mitigate train delays in the UK rail network. Integrating BN methods into transportation risk assessment significantly advances the understanding and management of train delays. Using extensive data from Network Rail, the study highlights the importance of addressing delays over 60 min due to their legislative and economic impacts. Adopting a predictive and proactive approach is crucial, especially during high-risk months identified by the study, with the model's alignment with actual weather data emphasising the need for robust, weather-responsive strategies. It reveals that severe flooding significantly impacts operational reliability, with December being the highest-risk month for delays due to EWEs, followed by January and July. The model also identifies a notable clustering of 80–90-minute delays, particularly on Fridays, suggesting a need for targeted regional interventions. By integrating various RIFs, the BN model enhances the precision of delay prediction and diagnosis. Furthermore, it provides insights into the interactions between variables such as train origin, destination, traction type, operator, incident reason, month, and schedule type. Targeted interventions, such as pre-emptive resource allocation, seasonal staff training, and infrastructure fortification, are essential for mitigating delays in high-risk periods and regions. The study's focus on a 60-minute delay threshold influences the regulatory framework for passenger rights, advocating for preventive measures over post-delay compensations, thus enhancing service reliability and passenger satisfaction. Operational risk assessment benefits from introducing new RIFs, particularly those related to weather incidents like flooding, and recommendations include evaluating fleet compositions and identifying Fridays as peak delay periods to refine scheduling and capacity management. Investments in weather-resistant materials, better drainage systems, and early warning technologies are recommended to strengthen rail infrastructure against weather incidents. This holistic approach to risk management enhances operational efficiency and passenger experiences, with the BN model's predictive capacity providing a strategic advantage for anticipating and preventing disruptions, ultimately driving economic gains and policy development.

Future research is recommended to integrate real-time data and qualitative inputs from experts to enhance the model's predictive accuracy and adaptability. This approach will facilitate a more dynamic response to evolving weather patterns, improving railway efficiency and passenger satisfaction under varied operational conditions. By refining the BN model and incorporating broader data sources, future investigations can offer a richer understanding of the factors driving train delays, supporting the development of robust, resilient railway systems equipped to handle the challenges posed by climate change. Beyond the applied UK case analysis, the generic BN risk model can be tailored to analyse weather-related train delays across a wider range of states worldwide, particularly those facing increased levels of climate impact.

CRediT authorship contribution statement

Leila Kamalian: Conceptualization, Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation. **Huanhuan Li:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Project administration, Methodology, Formal analysis, Conceptualization. **Mark Ching-Pong Poo:** Writing –

review & editing, Supervision, Formal analysis. **Ana Bras:** Writing – review & editing, Validation, Supervision. **Adolf K.Y. Ng:** Writing – review & editing, Validation, Supervision. **Zaili Yang:** Writing – review & editing, Visualization, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Zaili Yang reports financial support was provided by Horizon European Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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