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Master of Science by Research Thesis

Data-Driven Investigation of Delay Propagation in the UK Rail Network

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Abstract

The railway network plays a crucial role in supporting sustainable foundation for economic and social activity. Yet, as a complex system of systems, it is continuously affected by propagating disruptions that stall performance and undermine user trust. This study aims to establish novel insights into delay propagation dynamics triggered by local incidents in the UK railway network. To this end, a data analytics framework is proposed to reconstruct past delay propagation events using operational data sourced from the Rail Data Marketplace database. The framework comprises five modules that provide complementary perspectives on delay propagation dynamics. Applied to representative stations and incidents, this framework yields practical diagnostic insights and supports the data-driven identification of network areas that may benefit from targeted interventions. This work primarily aims to support future research on delay propagation forecasting by providing datasets against which simulation models can be validated, with the longer-term objective of enabling data-validated digital twins to support effective rail disruption management. In alignment with this objective, an open-source companion Python toolkit is released to facilitate wider adoption.

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1. Introduction

Transportation has consistently been at the forefront of economic and social development. It has enabled wider mobility in terms of the possible range of reachable places by various forms of transport, from the first wheel to air planes and railways. As technology in transportation rapidly evolved, distant places became shortly connected. Transport significantly contributed to the progress of civilisation, both as a result of emerging technological advancements and as a driving force behind them. With the expansion of modern technologies in society, the importance of reliable and high-capacity transport systems increases accordingly (Hale, 2013). Railways, in particular, have emerged as a cornerstone of national transport infrastructures, supporting economic growth by connecting cities, regions, and communities while offering an alternative to road-based transport (Osborne, 2024; Coates, 2025; Linear Recruitment, 2025).

The railway network of the United Kingdom (UK) is the oldest in the world. It has played a central role in shaping spatial development patterns and remains essential for commuting, long-distance travel, and freight movement (Mitchell, 1964). Throughout its development, railways have progressed in terms of the structural stability of the infrastructure, passenger capacity, operational reliability, and safety performance, to mention a few. In contemporary times, the network benefits from largely stable rolling stock fleet, the provision of modern passenger amenities, adherence to stringent safety regulations, and the operation of high-speed services (Brown, 2017). Moreover, approximately 39% of the UK railway network has been electrified, corresponding to around 6,200 km (Associated Society of Locomotive Engineers and Firemen (ASLEF), 2025), with ongoing plans to expand electrification as a primary energy source across the wider system. These plans have been formally published by Network Rail in September 2020 in the report Traction Decarbonisation Network Strategy (Network Rail, 2020). This report indicates a business proposal to have a 'net-zero' emissions rail infrastructure by 2050, with notable electrification projects that include the routes in Fife and the Borders, the Transpennine Route Upgrade (TRU) and East-West Rail.

Modern rail systems operate as complex, tightly coupled networks in which planned services must continuously adapt to fluctuating demand, infrastructure constraints, and incident uncertainties (Gibson et al., 2002; UK Parliament, House of Commons, 2025). While railways benefit from dedicated corridors and protection from some external disruptions typical of road transport, they remain highly vulnerable to a wide range of internal and external disturbances. These disturbances can include faults due to ageing assets, infrastructure failures, rolling stock malfunctions, signalling issues, staffing constraints, and extreme weather events (Armstrong, 2024). When such disruptions occur, their effects are rarely confined to a single service or location. Instead, delays propagate across interconnected routes, stations, and services, amplifying their impact over time and space. This cascading behaviour can result in widespread service delays and cancellations, overcrowding, reduced passenger safety and comfort, and increased operational costs (Office of Rail and Road, 2024; Department for Transport, 2025).

The consequences of delay propagation extend beyond immediate service performance. Prolonged or recurrent disruptions can undermine public confidence in rail transport, prompting modal shifts toward less sustainable alternatives such as private vehicles (Department for Transport & BritainThinks, 2019). From an operational perspective, delays often lead to inefficient resource utilisation, increased energy consumption, and heightened wear on infrastructure and rolling stock. These challenges further raise the complexity of timetable planning and network coordination in the management of the disrupted passenger flows (Department for Transport and Lord Hendy of Richmond Hill CBE, 2026). As a result, understanding how and why delays emerge and spread throughout the rail network is critical for improving resilience, long-term sustainability and passenger usage.

Addressing these challenges requires a comprehensive understanding of rail network operations. A national-scale rail network, however, is complex with numerous assets supporting its performance, such as physical track and station infrastructure, scheduling practices, electrical systems and signalling mechanisms. While existing studies have provided valuable insights into rail performance, they often rely on aggregated or simulated data, which may fail to reflect the real-world, network-level operational processes driving delay propagation (Evans and Berg, 2009; Hyland et al., 2016; McGuire and Linder, 2025). On the other hand, operational data, such as detailed records of train movements, schedules, and real disruption information, offer a practical representation of system dynamics. However, these data are rarely processed in a form suitable for understanding the complex mechanisms for rail delay propagation, hampering technical developments for effective rail disruption management.

This thesis proposes a data analytics framework to reconstruct past events of delay propagation in the UK rail network. To the best of the author's knowledge, this thesis represents the first known application of Rail Data Marketplace data to reconstruct delay propagation in the UK rail network. The proposed framework enables a data-driven investigation of rail disruption using operational records, differentiating from existing approaches that rely on simulated data. It is distinguished from other data-driven approaches that passively enumerate relevant data by actively mapping incident and delay records to reconstruct affected timetables. By applying the framework to selected historical events, the study further provides generalised insights on disruption dynamics.

The framework is published as an open-source toolkit, whose overall process from data processing to analysis modules is summarised in Figure 1.1. The five analysis modules provide complementary perspectives of the behaviour of the network under disruptions, with mutual relationships denoted by the arrows in Figure 1.1. The framework is designed to facilitate future developments, so that users can readily adopt it to create new links between modules depending on the analytical objective.

The thesis is organised as follows. Chapter 2 summarises the background of the UK rail network and reviews relevant research on rail disruption management. Chapters 3 and 4 describe the proposed data analytics framework. Specifically, Chapter 3 presents the datasets employed and the associated data processing workflow, while Chapter 4 introduces the five modules of the framework, each designed to provide complementary perspectives on delay propagation mechanisms. The practical application of these modules is demonstrated through selected examples of stations and incidents. Finally, Chapter 5 discusses general insights derived from the preceding investigations, followed by concluding remarks in Chapter 6. The companion Python toolkit is available at `https://github.com/martazarantonello/rdmpy`.

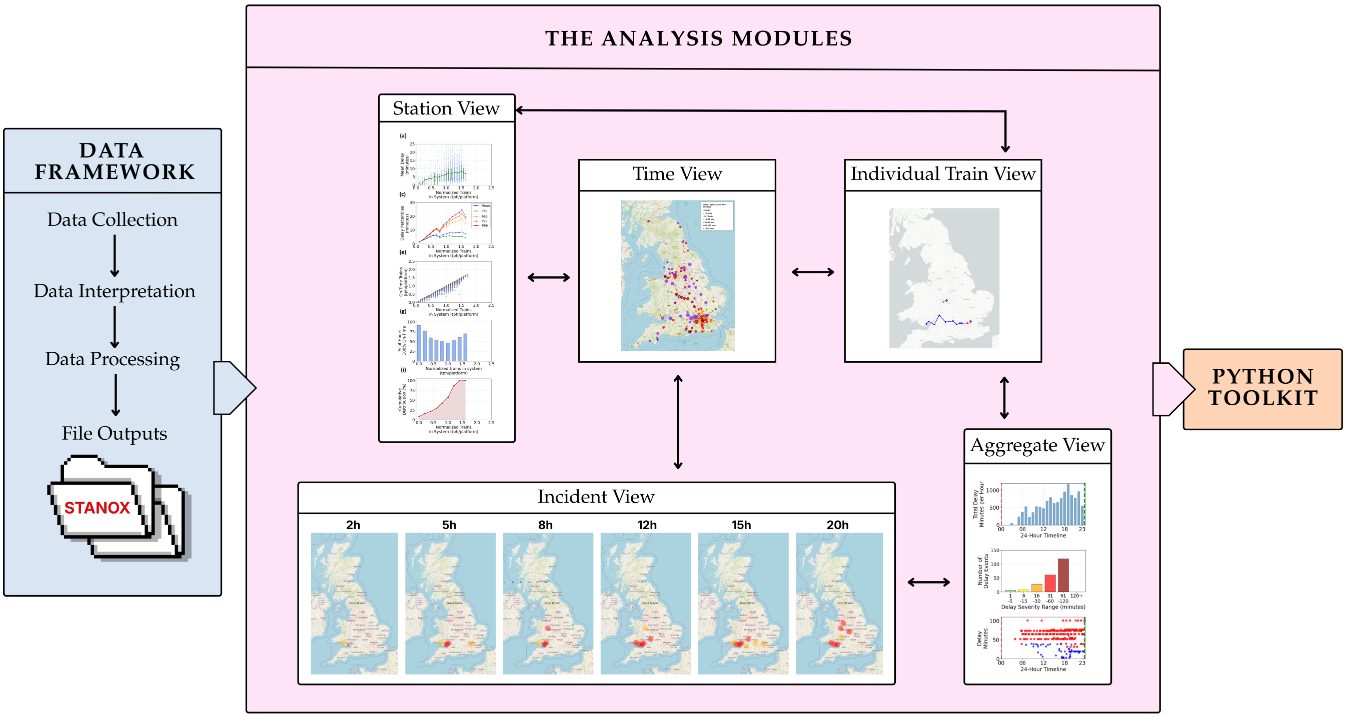

Figure 1.1: Workflow diagram of the framework proposed

2. Literature Review & Background

2.1 The UK's Rail Data Marketplace

This study leverages the UK's Rail Data Marketplace (RDM) as a primary data source. RDM is a digital platform established under the stewardship of the Rail Delivery Group to centralise access to rail-related data across the UK, addressing long-standing data fragmentation in the sector. It provides a unified access point where datasets published by train operating companies, Network Rail, and governmental bodies, enabling interoperable use of both real-time and historical rail data across research, operational, and commercial applications.

Beyond acting as a data catalogue, RDM functions as a hybrid data ecosystem that supports open-access and commercially licensed datasets, with mechanisms for controlled data sharing and licensing. This structure lowers barriers to data access while allowing provides to retain governance over their content, fostering innovation, operational transparency, and cross-sector collaboration. By bridging operational and research data domains, RDM reduces the cost and complexity of data acquisition, accelerates the translation of data insights into practical applications, and contributes to evidence-based decision-making, across the rail industry and research communities (Rail Delivery Group, 2026).

2.2 Resilience of Rail Services

2.2.1 Definition and Computation of Resilience

The built infrastructure has been the subject of numerous studies investigating its resilience. The concept of resilience was first introduced by Holling (1973) in ecological systems, defined as:

a measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables.

Since then, it has gradually evolved and applied in diverse disciplines. These include psychology (Masten et al., 2002; Butler et al., 2006), economics (Briguglio et al., 2006; Reggiani et al., 2002) and engineering (Woods and Wreathall, 2003; Woods, 2003; Little, 2003; Madni and Jackson, 2009; Hollnagel et al., 2006). New terminology keeps being adopted by researchers depending on their study's needs and domain of practice. Generally, the widely accepted United Nations (UN) definition frames resilience as:

the ability of a system, community or society exposed to hazards to resist, absorb, accommodate to, and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions (United Nations International Strategy for Disaster Reduction, 2009).

In transport and network studies, the concept is commonly adapted and extended to reflect system-specific characteristics and performance metrics, leading to a wide body of work across road networks (Omer et al., 2013; Zhang and Wang, 2016; Calvert and Snelder, 2018; Kasmalkar et al., 2020; Dong et al., 2025), air travel (Janić, 2015; Dunn and Wilkinson, 2016; Yoo and Yeo, 2016; Gössling, 2020; Weitz et al., 2026), waterways (Baroud et al., 2014; Hosseini and Barker, 2016; Wang and Yuen, 2022), and rail and metro systems (Chopra et al., 2016; Hale and Heijer, 2017; Lu, 2018; Bešinović, 2020). As a result of differing system objectives and analytical perspectives, no single unified definition of transport resilience has emerged (Bešinović, 2020). Instead, the literature converges on recurring themes captured by four core properties—robustness, redundancy, resourcefulness, and rapidity—which describe how systems withstand, respond to, and recover from disruptions (Bruneau and Reinhorn, 2006; Zhou et al., 2019). These properties are quantified through diverse resilience metrics, including topological metrics reflecting network structure (Mattsson and Jenelius, 2015; Adjetey-Bahun et al., 2016b; Wang et al., 2017; Li et al., 2026a), attributes-based metrics describing performance during specific disruption periods (Murray-Tuite, 2006; Beiler et al., 2013), and performance-based metrics evaluating system performance over the full disruption-recovery cycle (Chen and Miller-Hooks, 2012; Twumasi-Boakye and Sobanjo, 2018; Liao et al., 2018).

For rail networks, active research has been conducted for various sources of disruptions. These include the impacts of climate change and extreme weather events on infrastructure systems (Chan and Schofer, 2016; Woodburn, 2019; Jiao et al., 2021; Chen et al., 2025), as well as on the management of user flows during periods of disruption (Adjetey-Bahun et al., 2016a; Chen et al., 2022; Ma et al., 2024). Other studies focus on technical system failures, such as track buckling (Kish et al., 2013; Ngamkhanong et al., 2018b; Ngamkhanong and Kaewunruen, 2022; Agustin, 2025) and energy-related incidents (Cheng et al., 2020; Moraski et al., 2023; Kljaić et al., 2023; Ilalokhoin et al., 2023), or external attacks against the users (Bruyelle et al., 2014; Gregson-Green, 2018). In addition, some studies examine resilience only during major disruptive events. This is because extreme conditions trigger and cause extreme responses (e.g. system shutdowns or significant casualties) on the mechanisms of failure (Janić, 2018; Janoš and Pospíšil, 2025; Li et al., 2026b).

These studies have made significant contributions to the quantification of railway resilience metrics. However, the majority rely on simulated scenarios, with only a limited number integrating real operational data into their models. To illustrate the extent and nature of this reliance on simulation, Table 2.1 presents an overview of data sources and methodological approaches across a representative sample of rail resilience studies (De Martinis and Corman, 2018; Rungskunroch and Maneerat, 2025). This limitation is largely due to the scarce availability of high-quality operational data and the high costs associated with collecting such data specifically for research purposes (Walker and Strathie, 2016; Ghofrani et al., 2018; Wu et al., 2025).

Table 2.1 illustrates these simulation-based approaches. For instance, Chopra et al. (2016) rely entirely on synthetic network models to assess random node and link failures, while Hale and Heijer (2017) employ theoretical vulnerability analysis and topological metrics without operational data. Similarly, Adjetey-Bahun et al. (2016b) combine Ghana's network topology with simulated delay patterns to evaluate hypothetical service disruptions, and Chen et al. (2025) develop stochastic simulation models for extreme weather scenarios. Even studies examining specific failure mechanisms, such as Ngamkhanong and Kaewunruen (2022)'s investigation of track buckling, rely on laboratory simulations and thermal predictive models rather than field incident data.

In contrast, attempts to integrate real operational data remain limited. Li et al. (2026a) evaluates railway resilience for the high-speed rail network in China by using topological metrics supported by real train operation data, incorporating travel time and service frequency between station pairs across different disaster phases. While this approach improves realism compared to purely simulation-based studies, it does not incorporate real incident data records. Another notable example is Rungskunroch and Maneerat (2025), which presents a data-driven framework to assess risk and enhance safety within Thailand's railway network. The study employs incident-based records from the period 2009–2024, using machine-learning and probabilistic-modelling techniques to identify patterns in incident occurrence. These two examples, highlighted in Table 2.1, underscore the rarity of longitudinal, network-wide incident data in the resilience literature, a gap that leaves most resilience assessments dependent on researchers' own simulated scenarios rather than systematically collected operational evidence.

Table 2.1: Data sources and methodological approaches in rail resilience studies

Study	**Network/System**	**Data Source(s) & Methods**	**Disruption Type**
Chopra et al. (2016)	London metro	Real network topology + passenger flow data; percolation-based simulation framework	Multiple failure types
Hale and Heijer (2017)	UK railway operators	Qualitative framework; operator interviews & organizational analysis	Operational decision-making
Adjetey-Bahun et al. (2016b)	Paris metro	Comprehensive simulation (passenger flows, power, telecom, organizational subsystems)	System failures (modeled)
Chen et al. (2025)	Urban rail network (generic)	Stochastic simulation model	Natural disasters (simulated)
Ngamkhanong and Kaewunruen (2022)	Railway track (generic)	Artificial neural network (ANN) prediction; laboratory thermal simulation	Track buckling
Lu (2018)	Shanghai metro	Real network topology + real passenger volume data; resilience modeling	Operational incidents
Li et al. (2026a)	China high-speed rail	Real train operation data (travel times, frequency) + topological metrics; *no incident records*	Disaster phases (simulated)
Rungskunroch and Maneerat (2025)	Thailand national rail network	Real incident records (2009–2024); machine learning & probabilistic models	Actual observed incidents
Bešinović (2020)	Railway systems (systematic review)	Literature synthesis; conceptual framework development	Multiple disruption types

Despite these previous achievements, there is a general lack of well-coordinated disruption data that systematically captures incidents across the network, which further limits the use of operational data for resilience assessment (Tutcher et al., 2017; Zhang et al., 2022a; Fu et al., 2024). Moreover, such data have rarely been used as a foundation for exploring network dynamics, with incidents typically treated as isolated local events (Marsh et al., 2016).

2.2.2 The UK Railway: Structure & Operational Context

The UK has been credited as the crucible of the modern railway system. In the 19th century, a vast network of lines connected cities, ports, and industrial centres, driving commerce and mobility. Many of these routes were later reduced, particularly during the mid-20th century Beeching cuts (Gibbons et al., 2024), but the remaining lines now form the core of the contemporary railway network. Key routes include the East Coast Main Line (London to Edinburgh), West Coast Main Line (London to Glasgow), Midland Main Line (London to Sheffield), Great Western Main Line (London to Bristol), and the Cross Country routes linking regions across England and Scotland. These routes are shown in Figure 2.1 on a geographical map of the network.

UK railway stations are classified by the Department of Transport (DfT) into six main categories based on passenger usage and staffing levels (Network Rail, 2021). Category A stations are national hubs with over 2 million annual trips, exemplified by Birmingham New Street and London King's Cross. Category B stations are regional interchanges, also handling over 2 million trips, such as Guildford and Nottingham. Category C is divided into C1 and C2, representing important feeder stations with 0.5–2 million trips annually, including Grantham and Plymouth (C1) and Burgess Hill and Tamworth (C2). Category D stations are medium-staffed with 0.25–0.5 million trips, like Abergavenny and Penrith. Category E stations are small-staffed, serving under 0.25 million passengers, such as Deal and Oakham. Finally, Category F is split into F1 and F2 for small unstaffed stations, also under 0.25 million trips, with examples including Beccles and Bishop Auckland (F1) and Llanfairpwll and Winchelsea (F2). In total, the network comprises of approximately 2,600 stations (Network Rail, 2021).

The Office of Rail and Road (ORR) publishes quarterly statistics that provide comprehensive insights into the performance of the UK rail network. These reports present key measures of passenger rail service, including both punctuality and reliability, and offer comparative data across operators and time periods (Office of Rail and Road, 2025a). In the latest quarter (Q3 2025), covering 1 July to 30 September 2025, ORR reports that train reliability has improved, while punctuality has experienced a slight decline relative to the same quarter in the previous year.

The quarterly statistics include the total number of trains planned by each operator, with most operators recording an increase in planned services compared with the previous year. Train punctuality is assessed using two principal metrics. The "Time to 3" measure reflects the proportion of station stops where trains arrived on time or within three minutes of the scheduled arrival (Office of Rail and Road, 2025b); in the Q3 2025, this value was lower than in the corresponding period of the previous year. The “On Time” measure represents the percentage of station stops where trains arrived on time or within one minute of the scheduled timetable (Network Rail, 2026). For Great Britain as a whole, the On Time performance in the Q3 2025 was 66.8%, a decline of 0.9 percentage points relative to the same quarter in 2024 (Office of Rail and Road, 2025a). On the other hand, the Public Performance Measure (PPM), which indicates the percentage of trains arriving at their final destination within five or ten minutes of the scheduled time depending on the type of operator (Office of Rail and Road, 2025b), reported a value of 85.4% for Great Britain in the Q3 2025 (Office of Rail and Road, 2025a). This represents a modest increase of 0.2 percentage points compared with the same quarter in the previous year. In contrast, cancellations were lower in the same quarter than in the corresponding period of the previous year (Office of Rail and Road, 2025a).

Network Rail also publishes operation and infrastructure summaries, namely *Network Statement* (Network Rail Network Statement, 2025), which provides information on rail infrastructure and the terms and conditions for allocation of capacity and use. Network Rail has identified several key areas of congested infrastructure across England in their latest Network Rail Network Statement (2025). The most critical is the Castlefield Corridor (Castlefield Junction to Manchester Piccadilly East Junction), a major bottleneck due to multiple services sharing a two-track section, limiting timetable flexibility and amplifying delays. In this regard, Network Rail states that capacity improvements are planned in phases CS2 by 2026, CS3 in late 2020s or early 2030s. The West Coast Main Line South Fast Lines and Wrexham–Bidston lines face capacity limits, with infrastructure unable to accommodate additional services without impacting performance. The East Coast Main Line has pinch points at Kings Cross, Doncaster, and northern sections, with formal congestion declared in parts of the network. Emerging capacity concerns exist on the Anglia Route, North and West London Lines, and Cross Country routes, driven by passenger growth, freight traffic, and operational constraints.

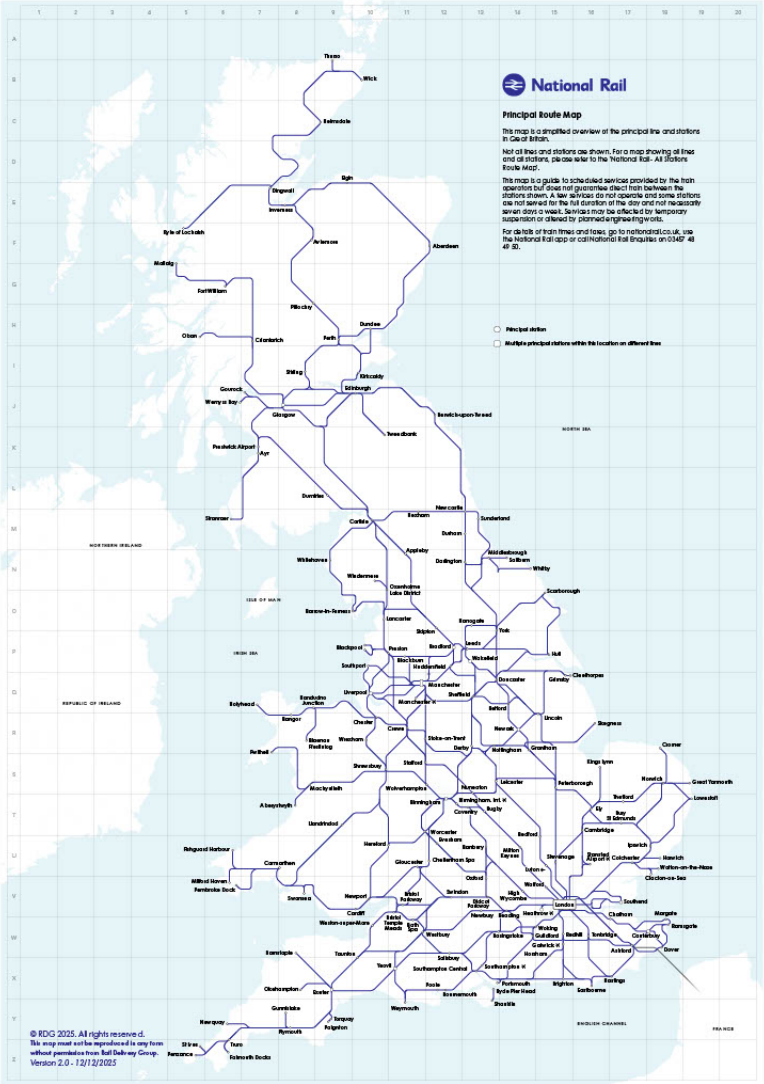

Figure 2.1: Map of the UK Railway Network. Source: National Rail (2026)

2.3 Understanding Rail Delay Propagation Mechanisms

2.3.1 Methods for Transport Simulation

In transport analysis, the most dominant methodology used to analyse delay propagation is mathematical modelling (Bešinović, 2020). *Optimization* and *analytic methods* (queuing theory) are two approaches that have been developed for the analysis of transportation networks. They are often complemented by simulation techniques, which are frequently employed to validate the proposed analytical models.

In recent years, these approaches have employed the support of computational intelligence (CI) and statistics (Karlaftis and Vlahogianni, 2011a), with their recent methodological advancements finding applications in transportation. These efforts can be referred to as *data-driven methods*. A range of classical statistical approaches has been used in the data analysis of transport networks, including regression-based models (Briggs et al., 2000; Shen and Aydin, 2014; Pun et al., 2019), survival analysis (Mishra et al., 2023; Nalin et al., 2024), time-series modelling (Quddus, 2018; Borucka and Guzanek, 2022), and probabilistic risk assessment (Soeanu et al., 2015; Haghighi et al., 2018). These methods have been particularly applied in passenger demand estimation and infrastructure performance evaluation. Another application has involved the analysis of delay propagation throughout the railway network, as detailed in Table 2.2.

Table 2.2: Methodological approaches to delay propagation analysis in railway networks

Modelling Approach	**Researchers**	**Key Contribution**
Stochastic propagation modelling	(Meester and Muns, 2007; Büker and Seybold, 2012)	Theoretical frameworks using phase-type distributions and stochastic processes to model delay propagation mechanisms in large-scale networks
Algorithmic and empirical analysis	(Goverde, 2010; Cerreto et al., 2018; Büchel et al., 2020)	Computational algorithms and data-driven methods for identifying delay patterns and quantifying propagation dynamics in operational railway systems

This application is particularly relevant to the present study, as delay propagation mechanisms is the focus of this investigation. These works have contributed to analysing how disturbances propagate spatially and temporally, supporting the reconstruction of network dynamics.

Beyond traditional statistical methods, CI has been increasingly adopted to address the complexity and uncertainty inherent in transport systems (Karlaftis and Vlahogianni, 2011b). CI encompasses a range of data-driven techniques that support learning and adaptation, including neural networks, fuzzy logic systems, evolutionary algorithms, and graphical models (Sadek et al., 2003; Engelbrecht, 2007; Scarselli et al., 2008; Bhatti et al., 2023). These approaches have been applied in transport research for traffic and demand prediction, incident detection, asset condition assessment, and disruption management.

There are many differences and common aspects between these two data analysis methods, both in the used terminology and framework. A key difference between statistics and CI lies in the learning process (Ansari and Hou, 2012). Unlike classical statistical models, which yield a single final model with an assumed functional form, CI training can converge to multiple, non-nested solutions, making CI more flexible. This flexibility comes at the cost of interpretability, as inference mechanisms and implicit data assumptions are often hidden, leading to concerns about reproducibility and the characterization of CI applications as “black boxes" (Cheng and Titterington, 1994; Warner and Misra, 1996; Karlaftis and Vlahogianni, 2011b). Moreover, CI development and training are typically more time-consuming than simpler statistical models (Patwary et al., 2018).

Despite these differences, statistical methods and CI can be combined into a powerful and complementary methodological framework. CI offers flexible representations of traditional statistical constructs, while statistical tools contribute rigour through estimation methods, uncertainty quantification, and model diagnostics (Nguyen et al., 2018). Together, they complement each other in core model development and large-scale data analysis. Another complementary application concerns the investigation of correlation and causal relationships (Pearl and Bareinboim, 2011; Graham, 2025). In this context, Bayesian networks represent a further complementary approach, integrating probabilistic inference, structural learning, and interpretability (Janssens et al., 2006; Lee et al., 2023).

Most of literature uses data that was either specifically collected for the study’s purpose, or assumed given the chosen network (Khalid et al., 2018). In practice, both approaches limit the applicability of the results, as they depend on controlled datasets or idealised assumptions that are difficult to obtain, maintain, or replicate in real-world operational settings (Wang and Zeng, 2018). Consequently, approaches that perform well under controlled or assumed conditions may face significant challenges when transferred to real-world transport systems. These constraints further contribute to a gap between methodological developments and their practical use. The reliance on tailored or assumed data often requires detailed system knowledge that is not always accessible to researchers working outside operational environments. At the same time, acquiring and sustaining such data in practice can be costly, resource-intensive, and, in some cases, infeasible due to organisational or data-access limitations.

This study addresses these limitations by leveraging extensive operational datasets available from the RDM database. Developing a consistent framework to reconstruct past events of dynamic delay propagation would enable the integration of CI and traditional statistical techniques. Statistical methods can be used to establish baseline delay behaviour and quantify uncertainty, while CI techniques can extract information from data to further calibrate model bias.

2.3.2 Advances in Railway Disruption Management

Railway systems are complex systems of systems that interface with the public and external hazards, making them especially vulnerable to disruption. Their reliability and performance can be compromised by both minor and large-scale incidents, which may occur concurrently. As a result, research has sought to enhance both network-wide operations and structural-specific advancements.

Early work has focussed on establishing common ontologies to facilitate communication between operational teams and researchers (Tutcher et al., 2017; Tatarelli et al., 2017; Alzahrani and Easton, 2025). Alongside this, other studies have explored predictive models to anticipate incidents before they occur, often leveraging machine learning techniques to identify patterns and early warning signals in operational data (Hadj-Mabrouk, 2020; Chen et al., 2024). A further strand of research has focussed on enhancing operational performance and network efficiency through timetable optimisation for capacity management and infrastructure maintenance planning (Caimi et al., 2017; Zhang et al., 2022b).

A growing body of literature addresses the effects of weather-related disruptions on rail performance. Extreme events such as rainstorms, flooding, high winds, and heatwaves can severely impact track geometry, overhead lines, and signalling systems, potentially causing widespread delays or service suspensions (Zhang and Lee, 2008; Wang et al., 2020; Hong et al., 2021). High winds, for instance, can compromise overhead line equipment stability and limit train speeds for safety reasons, while heavy rainfall and flooding may lead to track substructure erosion, track buckling, or temporary closures (Doll et al., 2014; Ngamkhanong et al., 2022; Lorenz et al., 2025). Research increasingly combines weather data with predictive maintenance and monitoring frameworks to anticipate periods of heightened risk and reduce the likelihood of delay propagation.

Alongside hazard prediction, track inspection and maintenance have been a central focus. Early work in track monitoring, for example, has focused on predicting failures along steel track segments, while more recent efforts have incorporated advanced sensing, data analytics, and predictive algorithms to anticipate degradation and prevent service interruptions (Ngamkhanong et al., 2018a; Malekjafarian et al., 2019). Automated inspection systems, sensor networks, and condition-monitoring technologies are now widely deployed to identify potential failure points before they result in operational incidents (Wang et al., 2011; Mittal and Rao, 2017; Sol-Sánchez et al., 2021). Integrating weather data into these systems further enables operators to target inspections to periods and locations of highest risk, improving overall resilience and reducing maintenance costs.

Equally important is research on recovery strategies and service rescheduling. When disruptions occur, minimising the impact on passengers and freight operations requires dynamic adjustment of timetables, re-routing of trains, and strategic prioritization of services (Glickman, 1983; Corman et al., 2010; Reynolds et al., 2020). In this regard, other models have been developed to optimize recovery and rescheduling, seeking to maintain service continuity while ensuring safety and efficiency (Meng and Zhou, 2014; Sun, 2020). These efforts often incorporate commuter demand patterns and network topology to guide operational decisions under uncertainty.

Understanding and predicting passenger and freight flows is critical to effective network management. Studies examining commuter flows often adopt a OD perspective, focusing on aggregate demand, congestion points, and delay propagation throughout the network (Stoilova, 2020; Yang et al., 2023). Freight operations, though less sensitive to short-term passenger demand, are highly dependent on reliable network performance to maintain supply chains (Barta et al., 2012). In literature, these publications are scarce, as data availability is highly sensitive within private sectors, which often operate freight trains. Companies are generally reluctant to share detailed operational data due to concerns over commercial confidentiality, competitive advantage, and the potential exposure of proprietary strategies.

In parallel, the emergence of digital twins represents a significant advancement in railway research (Gao et al., 2021; Ghaboura et al., 2023). A digital twin can be defined as:

> *a dynamic digital representation of a physical asset, system, or process, continuously updated with real-time data, and capable of simulating, predicting, and optimizing performance throughout its lifecycle* (Tao et al., 2018; Jones et al., 2020; Singh et al., 2021).

Digital twins have been increasingly applied to railway infrastructure for monitoring (Kampczyk and Dybeł, 2021; Ahmad et al., 2024), predictive rail bridge maintenance (Kaewunruen et al., 2022), and scenario testing (Chacón et al., 2024). They allow operators and researchers to simulate disruptions, evaluate mitigation strategies, and optimise resource allocation without direct intervention in the physical network. However, despite their promise, digital twins often face the challenge of limited high-resolution operational data. Many existing studies focus on model development, validation, and scenario simulations rather than deriving insights from real operational datasets. This limitation underscores the value of projects that leverage real-world operational data. By directly analysing operational information, it becomes possible to study delay propagation, network vulnerability, and resilience in a way that complements model-driven approaches and provides actionable insights for both research and practice.

In this context, the present research focuses on establishing a data analytics framework that extracts system-level insights directly from operational data. The framework is intended to support the aforementioned research efforts by providing both a methodological foundation and a Python toolkit for reconstructing past incident-driven delay propagation dynamics. The resulting datasets can, for example, be used for validating digital twin methodologies for delay propagation and compensation costs.

3. Data Investigation Framework

3.1 Delay Attribution and Schedule data

The delay attribution and schedule data are sourced from the RDM database, namely *NWR Historic Delay Attribution* and *NWR Schedule*. Both datasets are developed by Network Rail and require cleaning before being processed.

The NWR Historic Delay Attribution data can be accessed as .csv files and it displays delay attribution data linked to a specific train. In other words, this data is collected as the train is in operation, reporting when and where it is affected by delays. Moreover, it includes the incident reason that caused the delay, along with the time and location of the start of the incident. The train information incorporates the origin and destination dates and locations, the train service code and the delay minutes it was affected by. While the files include other attributes, they were not used for the objectives of this study.

The delay attribution dataset used in this study covers the financial years from 2023–24 P12 to 2024–25 P10. In UK rail industry financial accounting, 'P' denotes one of the 13 reporting periods that structure the financial year, with P12 and P10 corresponding to the calendar months from February 2024 to January 2025. Each record in this dataset represents a train that experienced a delay, including information on the train service, the delay duration in minutes, the reason for the delay, and the location and time at which the delay started. Notably, trains that operated on time are not included. A sample of the raw dataset is presented in Table A.1 in the Supplementary Materials A , illustrating the structure and typical entries.

The NWR Schedule data can be accessed as a .json.gz file. For this study, the file selected covers the fixed weekly train schedules for all train operating companies (TOC) as a full extract in daily formats. This source consists of five distinct datasets: header (metadata), location codes, train associations, schedule data, and end-of-file specifications. In this study, only the schedule data are extracted and used. At the time of download, this dataset represented the most recently published scheduling information and was structured on a train-centric basis. Each data entry includes the stations at which the train service is scheduled to call, together with the corresponding planned times. In addition, the dataset provides origin and destination locations and times, as well as the associated train service code. A sample of the raw dataset is presented in the in Table A.2 Supplementary Materials A, illustrating the structure and typical entries.

Unlike the delay attribution data, the schedule dataset is based on a fixed weekly timetable and remains consistent throughout a year. Consequently, individual records in this dataset do not have a natural temporal unit equivalent to that of the delay dataset. A key distinction between the two datasets lies in how location information is encoded: the delay records use STANOX codes, whereas the schedule records use TIPLOC codes. This difference in reporting, together with the fact that one dataset contains only delayed services while the other represents a complete weekly schedule, requires careful consideration during data processing. Specifically, it necessitates establishing continuity in data headers, columns, and types to ensure compatibility for subsequent analyses.

Although these datasets are comprehensive and rich in detail, their structure and terminology are primarily designed for operational use rather than direct analytical interpretation. As a result, several data fields required further research in order to be translated into more intuitive terms. For example, train delay was reported using the PFPI term, which in railway operations denotes Public Performance Failure Impact. This represents the number of minutes a service was delayed for. In addition, the delay dataset included records only for services that experienced delays, with no explicit representation of trains that operated on time. To address this limitation, the schedule data were used as a reference baseline and merged with the delay records. This integration enables the reconstruction and representation of a complete operational picture of the network.

3.2 Data Processing

Data preprocessing was conducted to remove records not related to the objectives of this study. This was a necessary methodological step due to the large size and complexity of the dataset. Subsequently, the processing step reconstructs the network's operations to capture both on-time and delayed services. For investigation, this study processes datasets during the period from February 2024 to January 2025. Specifically, this step maps the incident and the schedule datasets by matching origin and destination time and location as well as the day of week, across the two datasets. The processed data follows the same data structure and ontology as the NWR Historic Delay Attribution data (i.e. the incident datasets).

Table 3.1 shows an example after preprocessing and processing the datasets. The last column *Data Source* summarizes the data source of each entry. The *Matched* entries correspond to those data columns used for the purpose of matching these two datasets. The *DFT_CATEGORY* entry, which has been manually matched, refers to the Department of Transport category, which is classified into six categories based on passenger usage, service levels, facilities, and their strategic role within the rail network.

Table 3.1: Processed data: structure and example

Entry Column	**Entry Example**	**Data Source**
TRAIN_SERVICE_CODE	27936004	Schedule
PLANNED_ORIGIN_LOCATION_CODE	51531	Matched
PLANNED_ORIGIN_GBTT_DATETIME	0559	Matched
PLANNED_DEST_LOCATION_CODE	51311	Matched
PLANNED_DEST_GBTT_DATETIME	0619	Matched
PLANNED_CALLS	0559	Schedule
ACTUAL_CALLS	0602	Delay
PFPI_MINUTES	3.0	Delay
INCIDENT_REASON	TA	Delay
INCIDENT_NUMBER	68128.0	Delay
EVENT_TYPE	M	Delay
SECTION_CODE	52711	Delay
DELAY_DAY	MO	Delay
EVENT_DATETIME	09-DEC-2024 06:02	Delay
INCIDENT_START_DATETIME	09-DEC-2024 05:37	Delay
ENGLISH_DAY_TYPE	MO	Delay
STATION_ROLE	Intermediate	Schedule
DFT_CATEGORY	B	Manual
DATASET_TYPE	SINGLE_DAY	Schedule
WEEKDAY	MO	Schedule

3.3 Python Toolkit

To facilitate processing new datasets and further innovation, this study develops a companion Python toolkit. Beyond the results presented in this thesis, the toolkit supports analyses of additional stations, incidents, and dates, allowing users to reproduce key results, visualize disruption patterns, and evaluate station- and network-level performance metrics. Thereby, this study aims to to support adoption across a range of rail decision-making and research applications.

Figure 3.1 illustrates the toolkit structure, uploaded at `github.com/martazarantonello/RDM_analysis.git`. Each module includes their own demos and step-by-step guidance, illustrating how data can be processed, filtered, and aggregated to explore disruption dynamics. By providing this framework, the Python toolkit facilitates reproducible analysis, allowing researchers and practitioners to explore resilience, capacity limits, and vulnerability under varying operational conditions.

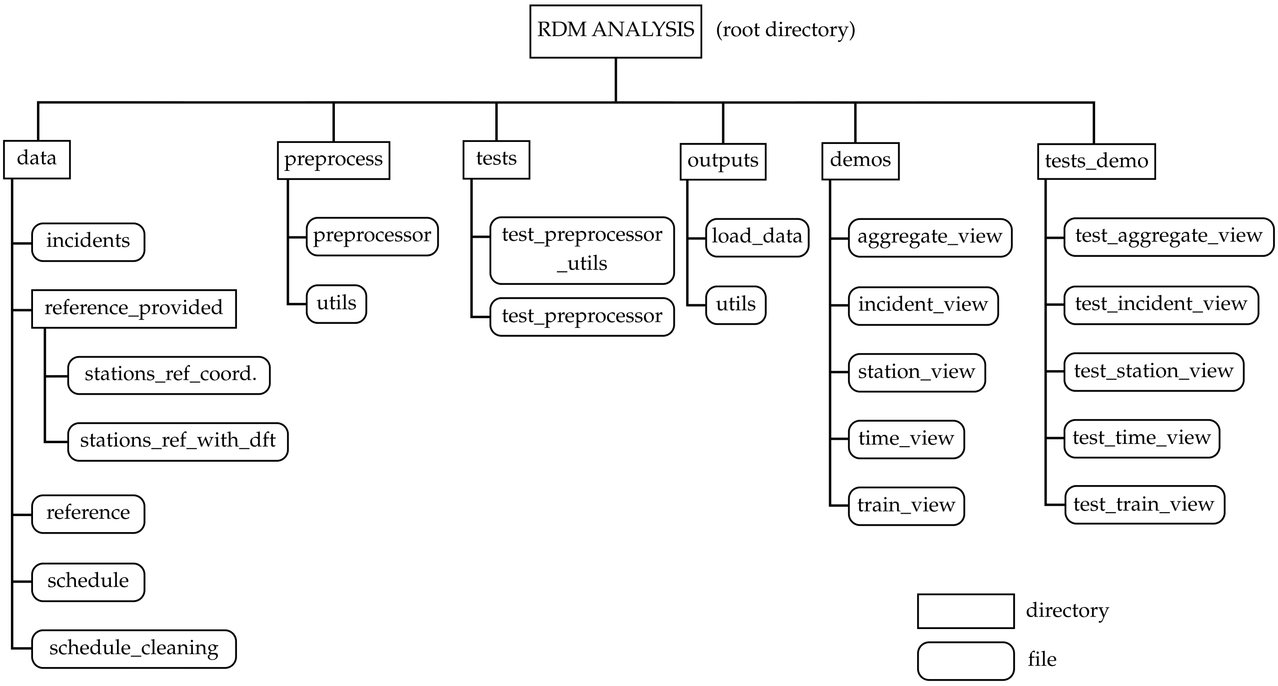

Figure 3.1: Tree structure of the Python toolkit: the input data are stored in the *data* folder, and after they are processed by the *preprocessor*, the *demos* showcase the five particular created views.

4. The Analysis Modules

4.1 Overview

Using the collated datasets described in Chapter 3, The five complementary modules are structured around distinct analytical viewpoints through which railway response to disruptions can be examined. Together, these modules capture different perspectives of the railway system and highlight the inter-dependencies that shape network behaviour. Their complementary nature allows them to be applied jointly, drawing on shared data to support a coherent and integrated analytical framework. Each module emphasises a specific perspective, ranging from spatially fixed elements of the network to temporal representations, allowing different facets of disruption dynamics to be isolated and analysed. The five views unfold as:

1. *Station View*
2. *Incident View*
3. *Aggregate View*
4. *Time View*
5. *Train View*

These five views are able to produce dashboards of the whole network in a variety of aspects. The aggregate view offers a high-level view of how a single rail incident impacts the wider network over time, and the incident view supports a geographical simulation on how a specific rail incident spreads across the network over time. This is done at a station-by-station basis. Following this, the station view is concerned with the evaluation of an individual station's performance, rather than being tied to a single incident number. This approach enables the examination of the relationship between train flow and delay. The fourth module, the train view, focuses on following a single train's journey on a particular day. The geographical view here produced shows the stations the train called at as well as all the incidents it encountered along the way. Their consequential delays are also included, making it a liable product for train assessment. Finally, the time view shows a spatial report of a day's worth of incidents and delays, mapping all the stations present in the network in both the numerical incident counts and the severity of delays there accumulated.

4.2 Station View

4.2.1 Module Description

The *Station View* module evaluates station-level performance using the most recent operational data which can be configured by the user (e.g. for six months). To provide a comprehensive view, the module provides four statistics: average, percentile-based, frequency-based, and cumulative metrics. They collectively illustrate a station's behaviour under varying operational loads. This is particularly valuable for comparing patterns of congestion and delay propagation across stations. By analysing station performance (i.e. on-time trains) as a function of operational load (i.e. tph/platform), the module enables inference under changes in operating conditions.

4.2.2 Case Study

The results shown are based on the most recent six months of published data, a time span selected specifically to enable validation of the analyses against operational information released by the relevant railway authorities. The Network Rail Network Statement (2025) is used to characterise the national rail infrastructure and the principles governing capacity allocation and access. Station performance is assessed using on-time indicators from On Time Trains (2026), a UK rail performance platform that aggregates and presents on-time train operations from openly available real-time and schedule data sources. In addition, the Network Rail (2024) Capacity Statement is considered as supplementary validation material, providing structured insight into network vulnerability characteristics and constraints. Although no longer a regulatory requirement, it remains a relevant reference for comparative assessment.

Four stations are selected and split into two groups derived from the proceedings of *OnTimeTrains* and Network Rail's Network Statements. Two stations belong to the best-performing group, Manchester Piccadilly and Milton Keynes Central, and two to the worst-performing group, Barking and London Cannon Street stations. The results of the best-performing and the worst-performing groups are presented in Figure 4.1 and Figure 4.2, respectively, which contrast mean delay behaviour, on-time train arrivals, and capacity utilization across hourly trains per platform, the *normalized trains in system*.

Figures 4.1**a**–**b** and 4.2**a**–**b** show the relationship between trains per hour per platform and mean delay minutes for the best and worst performing stations, respectively. In the best-performing stations, mean delay increases gradually and remains relatively low across the observed range, with a limited dispersion of individual delay observations. This indicates a stable operational regime in which rising demand does not cause disproportionate delay growth. By contrast, the worst-performing stations exhibit substantially higher mean delays even at moderate traffic levels, accompanied by a much wider spread of delay minutes. This dispersion suggests increased vulnerability and uncertainty under comparable loading conditions.

Further differences emerge in Figures 4.1**c**–**d** and 4.2**c**–**d**, where delay percentiles are compared. For the best-performing stations, the gap between median and extreme percentiles remains relatively constrained, implying that severe delays are infrequent and that performance degradation is fairly uniform. In the worst-performing stations, however, upper percentiles rise sharply as traffic intensity increases, with extreme delays escalating at a faster rate than central tendencies. This divergence highlights the presence of tail-risk behaviour, whereby a subset of services experiences disproportionately large delays as congestion grows.

Figures 4.1**e**–**f** and 4.2**e**–**f** relate on-time performance directly to system loading. In the best-performing stations, observed on-time train counts closely follow the theoretical reference line, indicating efficient utilization of capacity and a limited accumulation of lateness. The worst-performing stations consistently fall below the reference trajectory, reflecting a systematic loss of punctuality as demand increases. The growing deviation from the idealized relationship suggests that these stations reach their effective capacity earlier, beyond which additional services aggravate delay propagation.

The distributional perspective provided in Figures 4.1**g**–**h** and 4.2**g**–**h** reinforces these findings. Best-performing stations maintain a high proportion of hours with 100% on-time services across most traffic bins, with only a modest decline at the highest levels of demand. In contrast, the worst-performing stations show a pronounced reduction in fully on-time hours as normalized trains in system increase, with reliability deteriorating rapidly even before peak loading conditions are reached.

It is noted that a station's punctuality depends not only on its capacity but also on traffic loads. To investigate the effect of traffic loads, the cumulative distributions of the normalized number of trains are illustrated in Figures 4.1**i**–**j** and 4.2**i**–**j**. The particularly pronounced difference in train volume is between Figures 4.1**l** and 4.2**i**. In Figure 4.1, more than 80% of operating hours involve fewer than one train per platform, whereas Figure 4.2 shows that this condition is met in only around 55% of operating hours. As a consequence, Milton Keynes Central station exhibits better overall punctuality than Barking station, despite Barking station achieving higher punctuality at higher normalized train levels when comparing Figures 4.1**h** and 4.2**g**. This observation underscores the importance of aligning traffic loads with station capacity to maintain reliable operations.

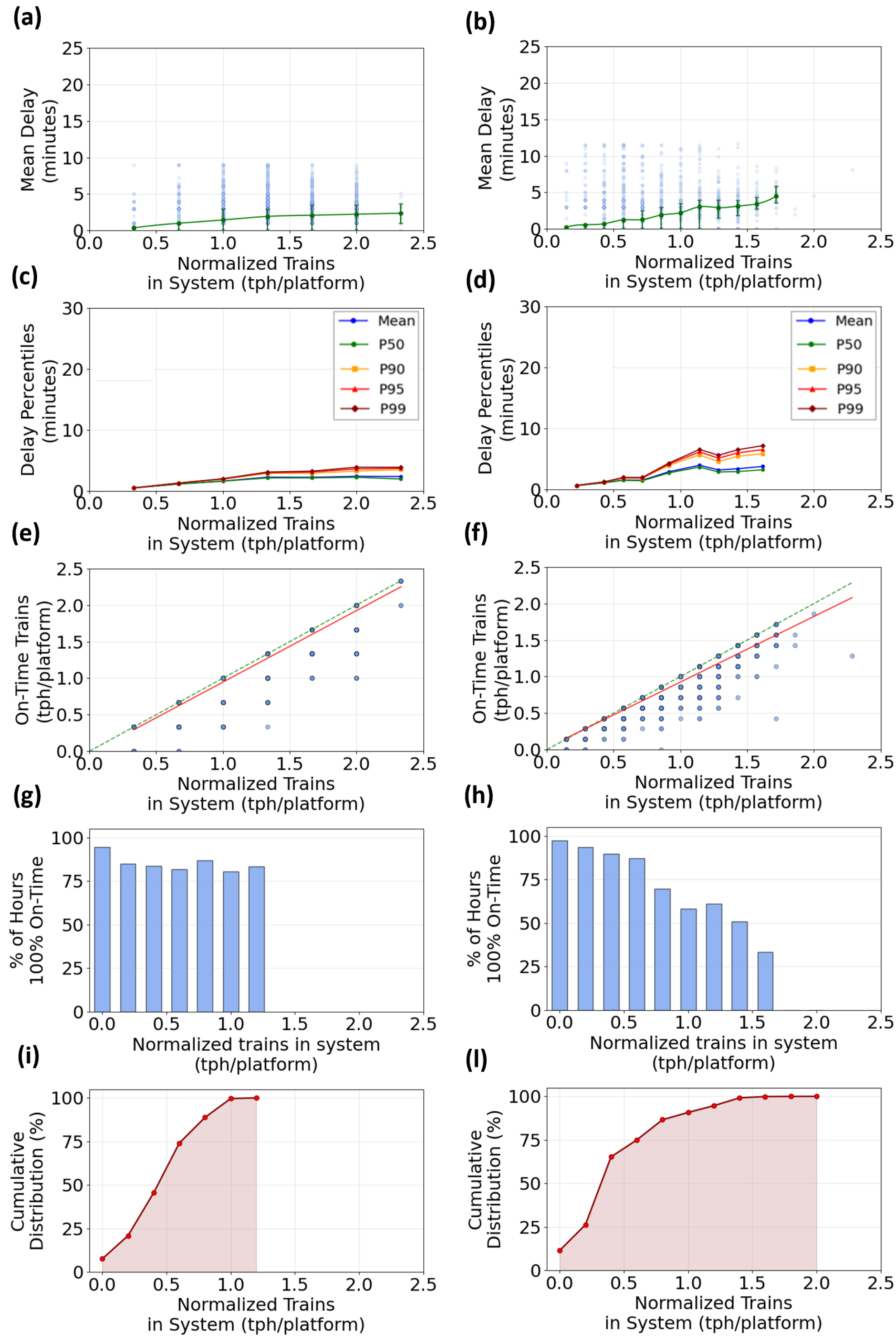

Figure 4.1: *Station View* illustrating Barking station on the left and London Cannon Street on the right. The graphs assess the normalised trains in system, as trains per hour per platform, and different parameters: mean delay in (**a**) and (**b**), delay percentiles in (**c**) and (**d**), on-time trains in (**e**) and (**f**), % of on-time hours in (**g**) and (**h**) and the cumulative distribution in (**i**) and (**l**).

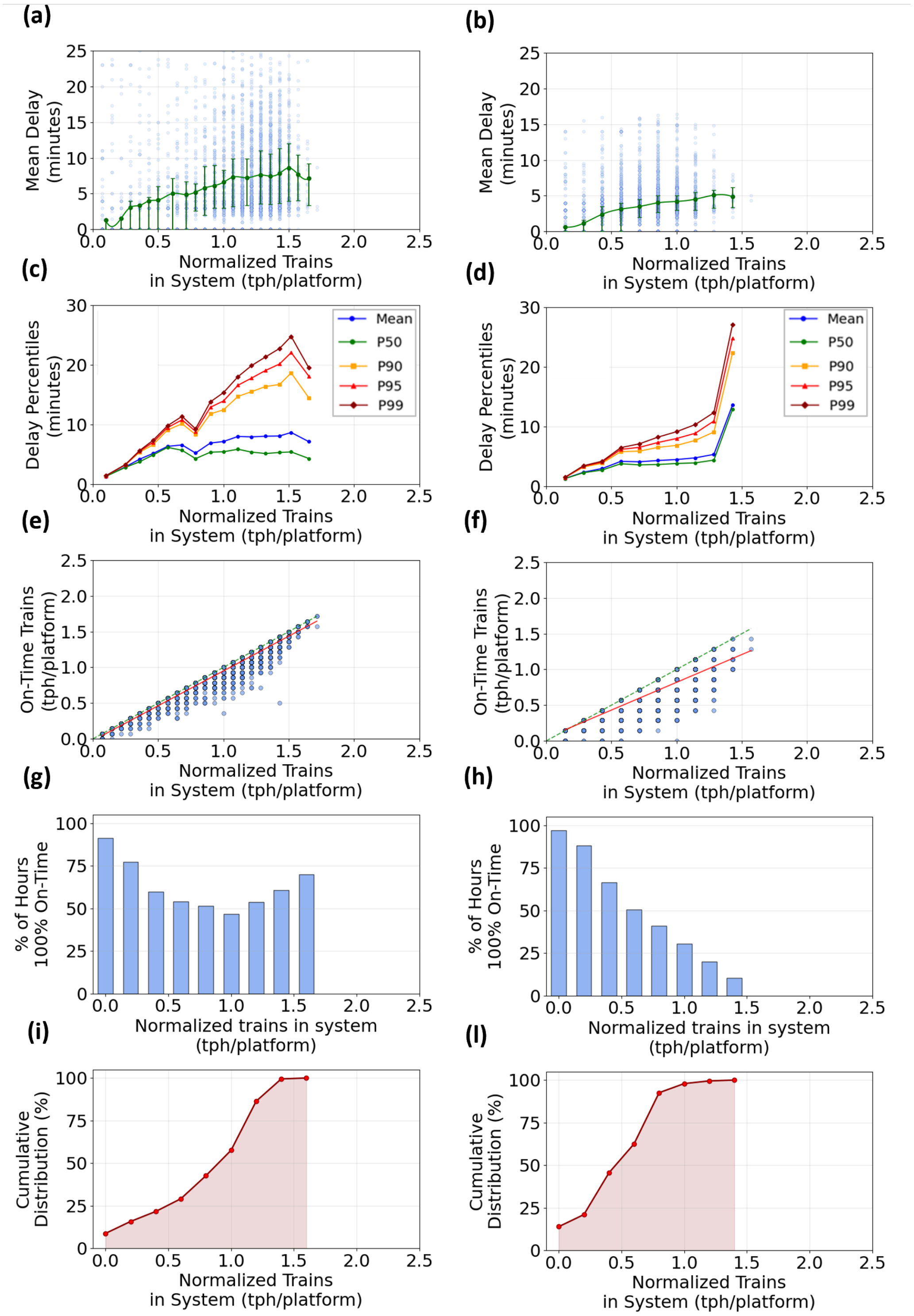

Figure 4.2: *Station View* illustrating Manchester Piccadilly station on the left and Milton Keynes Central on the right. The graphs assess the normalised trains in system, as trains per hour per platform, and different parameters: mean delay in (**a**) and (**b**), delay percentiles in (**c**) and (**d**), on-time trains in (**e**) and (**f**), % of on-time hours in (**g**) and (**h**). In (**i**) and (**l**) the cumulative distribution of normalised trains in the system is shown.

4.3 Incident View

4.3.1 Module Description

The *Incident View* module provides graphical view of impacts caused by a specific incident. For a selected incident code and date, this view maps the total delay minutes accumulated at each affected station over a defined temporal interval, which can be configured by the user (e.g., 10 minutes or 1 hour). This temporal aggregation allows for the examination of delay propagation dynamics across the network over time. In addition to delay accumulation, the module records the duration of the incident and its associated reason to provide contextual information that shapes disruption patterns.

By situating delays within the network topology, the view identifies the origin of the incident and traces its downstream effects across connected stations, highlighting nodes that experience disproportionately high disruptions or act as propagation bottlenecks. This view can be used to identify critical incident conditions (e.g. incident origins, causes, and times of occurrence) in terms of network-level delay propagation, as it enables comparing past events of delay propagation. It is also useful for validating the effectiveness of interventions (e.g. whether delay minutes decrease after maintenance work), adjusting timetables, or detecting operational changes.

4.3.2 Case Study

For illustration, Figures 4.3 4.4 and 4.5 examine six incidents that are organized into three paired comparisons based on spatial origin and incident reason. The first pair in 4.3 consists of two incidents originating in the Edinburgh area. The incident in 4.3**a** is associated with incident reason IR, referring to a broken/cracked/twisted/buckled/flawed rail, and happened on 28th April 2024. The other incident in 4.3**b** took place on 28th October 2024 with its incident reason I2, referring to AC/DC trip, including no fault or cause found. Although both incidents affect a similar geographic region and infrastructure causes, their impacts differ. One incident remains relatively contained, with delay occurrences confined to a limited number of stations that are close to the incident location. In contrast, the second incident propagates across a broader section of the network, producing higher delay totals and affecting a larger number of stations. This comparison highlights how incidents with similar spatial origins can generate markedly different disruption extents.

The second pair is in Figure 4.4 where both incidents originate in the Cardiff area. The incidents share the same incident reason code, XW, which stands for High Winds. This corresponds to the extreme weather conditions associated with Storm Darragh that hit the Southern coast of the UK on 7th December 2024. The incident in 4.4**c** took place on the first day of the storm, 7th December 2024, while the incident in 4.4**d** took place two days later on 9th December 2024. Both incidents exhibit similar spatial propagation patterns, with delays extending north-eastwards through the lower and central portions of the network. In both cases, impacts reach as far as London, while remaining geographically bounded and not extending beyond station. Despite differences in total delay magnitude between the two incidents, the similarity in their spatial footprints suggests a consistent network response to extreme weather conditions affecting this region.

The third pair is shown in 4.5. The first takes place on 16th September 2024 and the second one takes place on 23rd July 2024. These incidents also originate in the Cardiff area but they are associated with a different incident reason code from those in 4.4**c** and 4.4**d**. Specifically, the code is MS, referring to planned underpowered or short-formed services. Unlike the wind-related incidents, both events remain highly localized, with disruptions are observed only near Cardiff. This consistency across different cases indicates that incidents of this type tend to produce limited spatial impacts, in contrast to weather-driven disruptions.

Taken together, these comparisons demonstrate how the Incident View supports the differentiation of disruption patterns based on both incident location and underlying cause. By disentangling the complex relationships between localized and network-wide impacts, the paired analysis indicates both variability and recurring structure of delay propagation patterns.

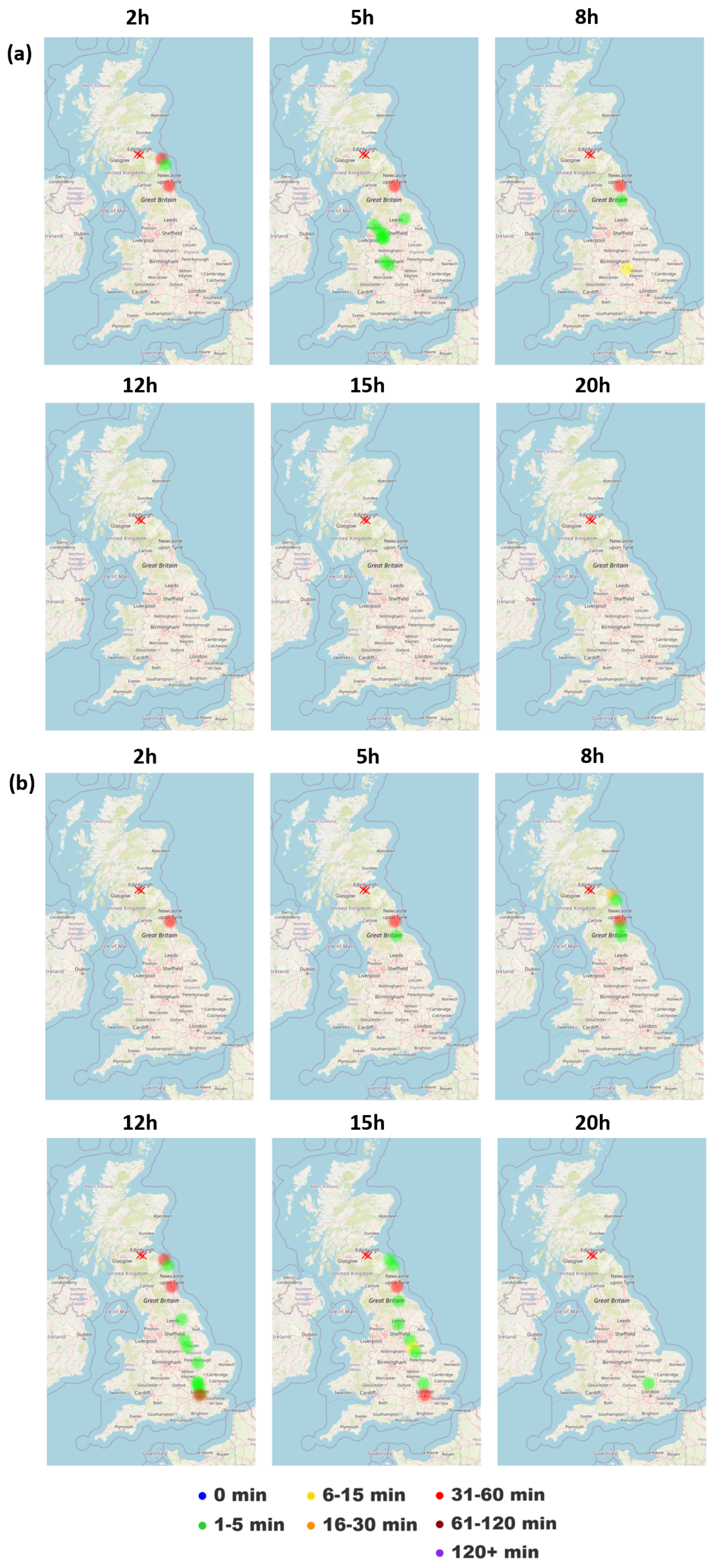

Figure 4.3: *Incident View* illustrating the impacts caused by an incident in 6 snapshots: (**a**) and (**b**) for two incidents from Edinburgh. Initial incident locations are indicated by a red cross in each figure. From left to right, the figures represent the impacts after 2, 5, 8, 12, 15 and 20 hours after the start of the incident.

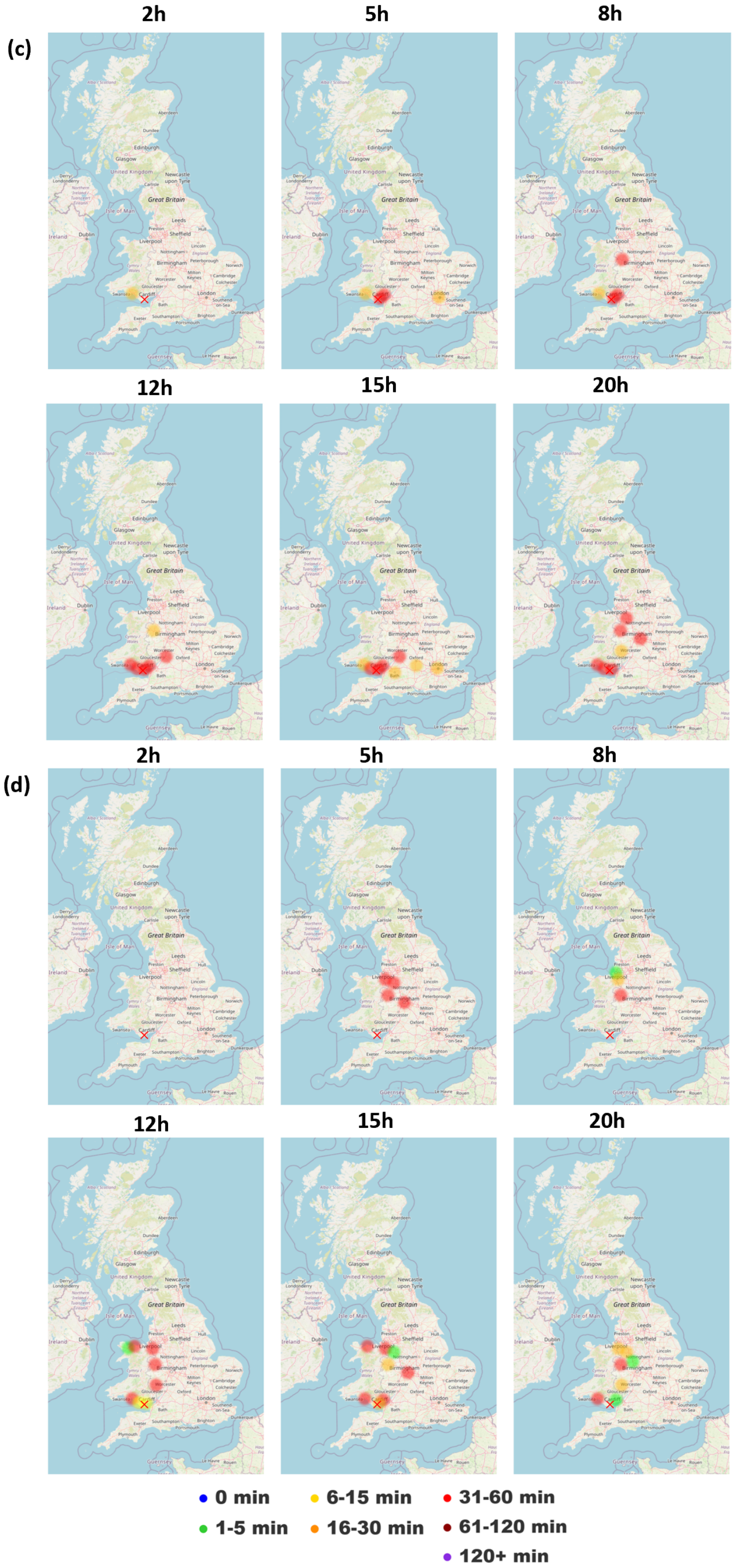

Figure 4.4: *Incident View* illustrating the impacts caused by an incident in 6 snapshots: (**c**) and (**d**) for the pair of incidents in Cardiff due to Storm Darragh. Initial incident locations are indicated by a red cross in each figure. From left to right, the figures represent the impacts after 2, 5, 8, 12, 15 and 20 hours after the start of the incident.

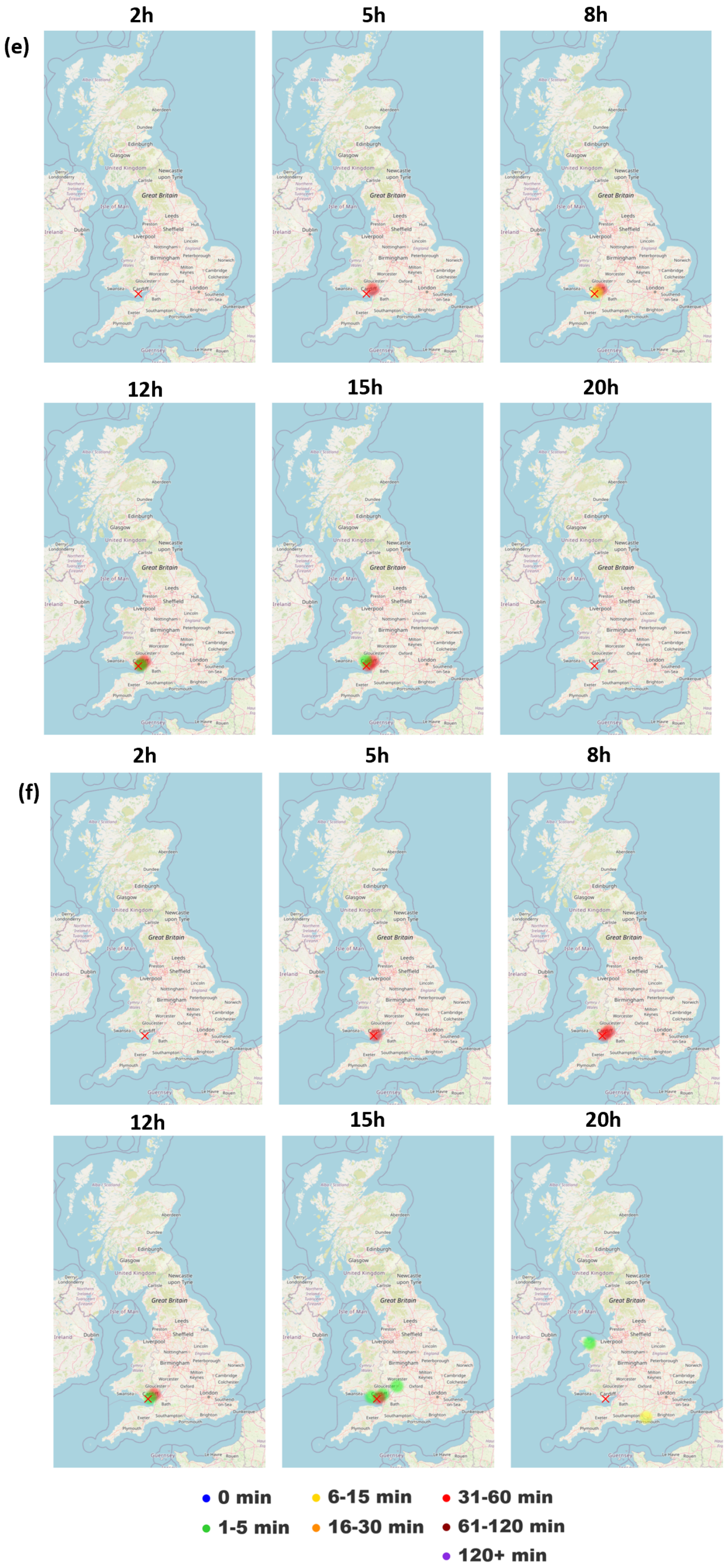

Figure 4.5: *Incident View* illustrating the impacts caused by an incident in 6 snapshots: (**e**) and (**f**) for two incidents from Cardiff due to planned disruptions. Initial incident locations are indicated by a red cross in each figure. From left to right, the figures represent the impacts after 2, 5, 8, 12, 15 and 20 hours after the start of the incident.

4.4 Aggregate View

4.4.1 Module Description

The *Aggregate View* module processes an incident code and date as input to produce a general report of the corresponding incident. Both inputs are necessary because incident codes are not unique across dates. This report provides a high-level overview of the incident's impact across the railway network. Specifically, the report illustrates three metrics: the number of cascading delay events throughout the day, the number of delay events by severity level, and the temporal distribution of delay minutes and cancellations across the day. These metrics enables comparing incidents in terms of their network-level impacts.

This view enables the assessment of delays' behaviour from the start of the incident to its end, hence displaying their propagation throughout the network. It also summarises the range of severity level ranging from minor delays to critical ones, where the range is defined consistently with the *Incident View* (c.f. Section 4.3). Reporting the magnitude of delay minutes, along with the trains that were ultimately cancelled, displays an added layer connected to the operational choices during disruptions.

4.4.2 Case study

For illustration, Figure 4.6 examines two incidents: incident *499279*, which occurred on 24th May 2024 in Edinburgh, and incident *62537* on 7th December 2024 that took place in Cardiff Central. These two incidents were chosen to draw comparisons between a notable disrupting event, Storm Darragh during 6th and 7th December 2024, and a minor incident with limited systemic impact on 24th May 2024, facilitating examination of disruption dynamics across different scales of severity. Specifically, the 499279 incident reports the incident reason code MD, referring to mechanical or fleet engineering causes below the solebar. The 62537 incident reports the incident reason code XW, referring to high winds affecting infrastructure the responsibility of Network Rail including objects on the line due to the effect of weather.

Figures 4.6**a**–**b** illustrate the relationship between the incident's onset and resolution, alongside the evolution of service disruptions. In Figure 4.6**a**, disruptions kept a minor magnitude whilst persisting from the onset to the conclusion of the incident, with a temporary cessation of delay occurrence between approximately 10:00 am and 1:00 pm. In contrast, Figure 4.6**b** shows markedly different patterns. Beginning shortly after midnight, the total accumulated delays increased progressively throughout the day, reaching their peak at around 7:00 pm.

Figures 4.6**c**–**d** further highlight their contrasting severity profiles. For incident 499279, delays predominantly fall within the minor to moderate severity categories, with an average delay of approximately 17.3 minutes. By contrast, incident 62537 exhibits markedly significant severity, with the majority of delays classified within the major and severe categories. This shift towards high-severity events leads to a substantially larger average delay of 54.6 minutes, and the presence of delay events exceeding 120 minutes further highlights its significant operational consequences.

Figures 4.6**e**–**f** visualize individual delay durations throughout the 24-hour timeline, together with cancelled services. The disparity between the two incidents is apparent. Incident 62537 is characterized by a dense cluster of cancellations (marked in red), distributed throughout most of the day. On the other hand, incident 499279 caused comparatively sparse cancellations, with delays generally lower in magnitude and occurring intermittently.

It is noted that, for both incidents, cancellations often occur after prolonged delays. This is illustrated in Figures 4.6**e**–**f**, where the red points representing cancellations appear at higher values along the y-axis, in some cases up to 100 minutes. This pattern suggests that cancellation decisions were made only after substantial delays had occurred, which would have compounded the inconvenience for passengers by limiting opportunities for finding timely alternative travel options.

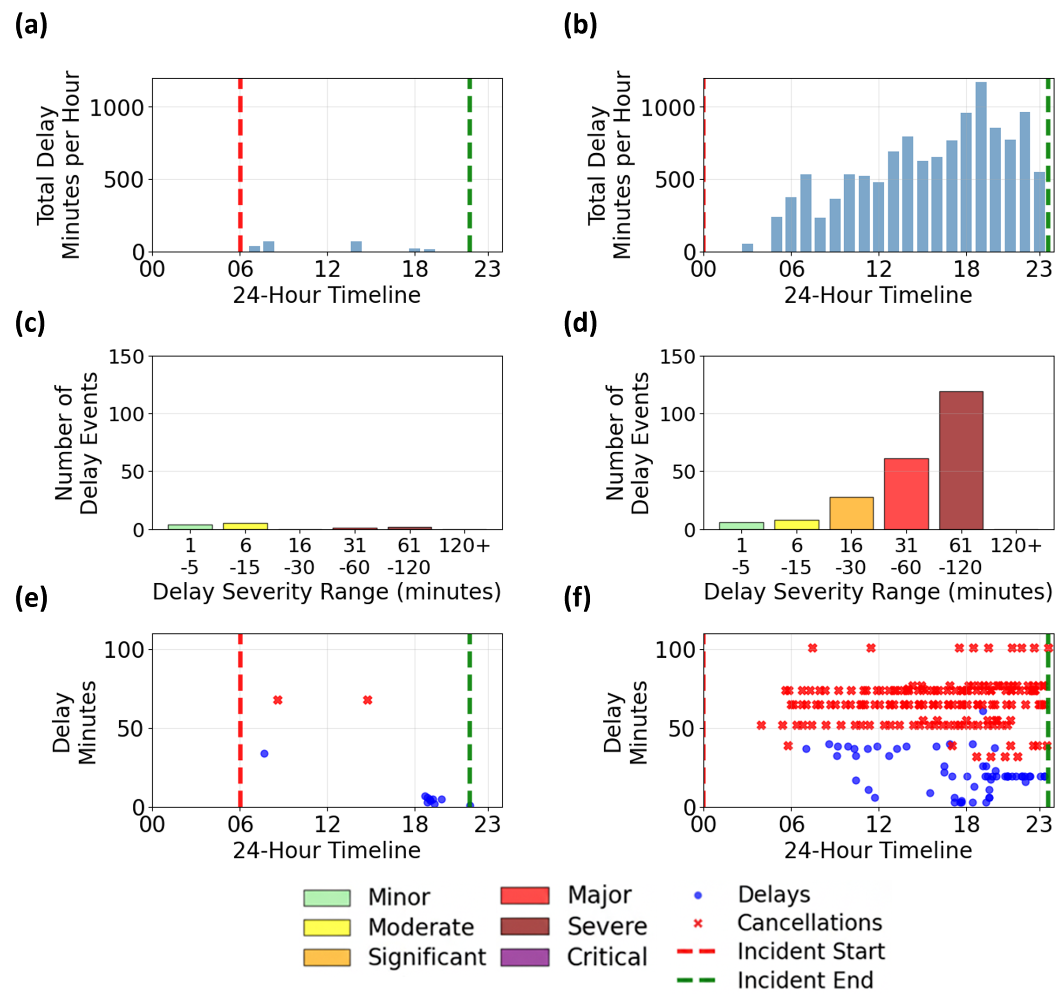

Figure 4.6: *Aggregate View* illustrating the impacts caused by the two incidents: (**a**) and (**b**) showcase the total delay minutes per hour, (**c**) and (**d**) showcase the delay severity range, (**e**) and (**f**) the delay minutes and cancellations occurring throughout the day. Incident *499279* is on the left and incident *62537* is on the right. While incident 62537 lasted for more than 24 hours, a fixed 24-hour timeline is used to facilitate comparison.

4.5 Individual Train View

4.5.1 Module Description

The *Train View* module focuses on the performance of an individual train in order to provide a service-centred perspective that complements the preceding station- and network-level analyses. Using a train identifier and a date as input, this module traces the train's journey across its scheduled stations, reporting deviations from the planned timetable. The total delay at each station and the sequence of incidents affecting the train are explicitly represented, so that one can assess the propagation of disruption along the train's route.

4.5.2 Case Study

For illustration, Figure 4.7**a** and **b** examines two train services: train *21700001* on 7th December 2024 and train *25375002* on 9th November 2024, respectively. The visual representation tracks the train's journey across all scheduled stations, highlighting the delays experienced at each station. Stations are represented as circles and are coloured by severity related to their experienced delays. Blue lines represent the geographic connectivity between consecutive stations and are shown as straight-line connections. This simplified representation may differ from the true alignment of the tracks. Incidents are shown as numbered purple circles (with 1 denoting the earliest event), while track-section incidents are represented by purple line segments. For train 21700001, the service experiences a sequence of more substantial delays, with multiple stations affected by major to severe delays, reflected in larger markers and darker colouring. This demonstrates a more consistently disrupted journey, with multiple incidents affecting different track sections, as indicated by the purple lines. In contrast, the train service 25375002 experiences moderate and sporadic delays, with only two stations showing higher delay accumulation, indicating localized disruption along the route. This may be because the service was affected by station-based incidents rather than track-based ones.

The numbered markers indicate the chronological order of incidents affecting each train, enabling assessment of how delays accumulate along the service. In particular, Figure 4.7**a** exhibits a higher density of incident markers, including multiple disruptions occurring at the same location (e.g. incidents 6 and 9), indicating repeated impacts on the same network segment. These observations highlight variability in train-level disruption: while some sections of the service experience only isolated and spatially dispersed delays (e.g near London area), others are subject to sustained and recurrent disruptions (e.g. York area). The comparative analysis underscores the value of the *Train View* in identifying routes and locations that are particularly vulnerable to repeated delays.

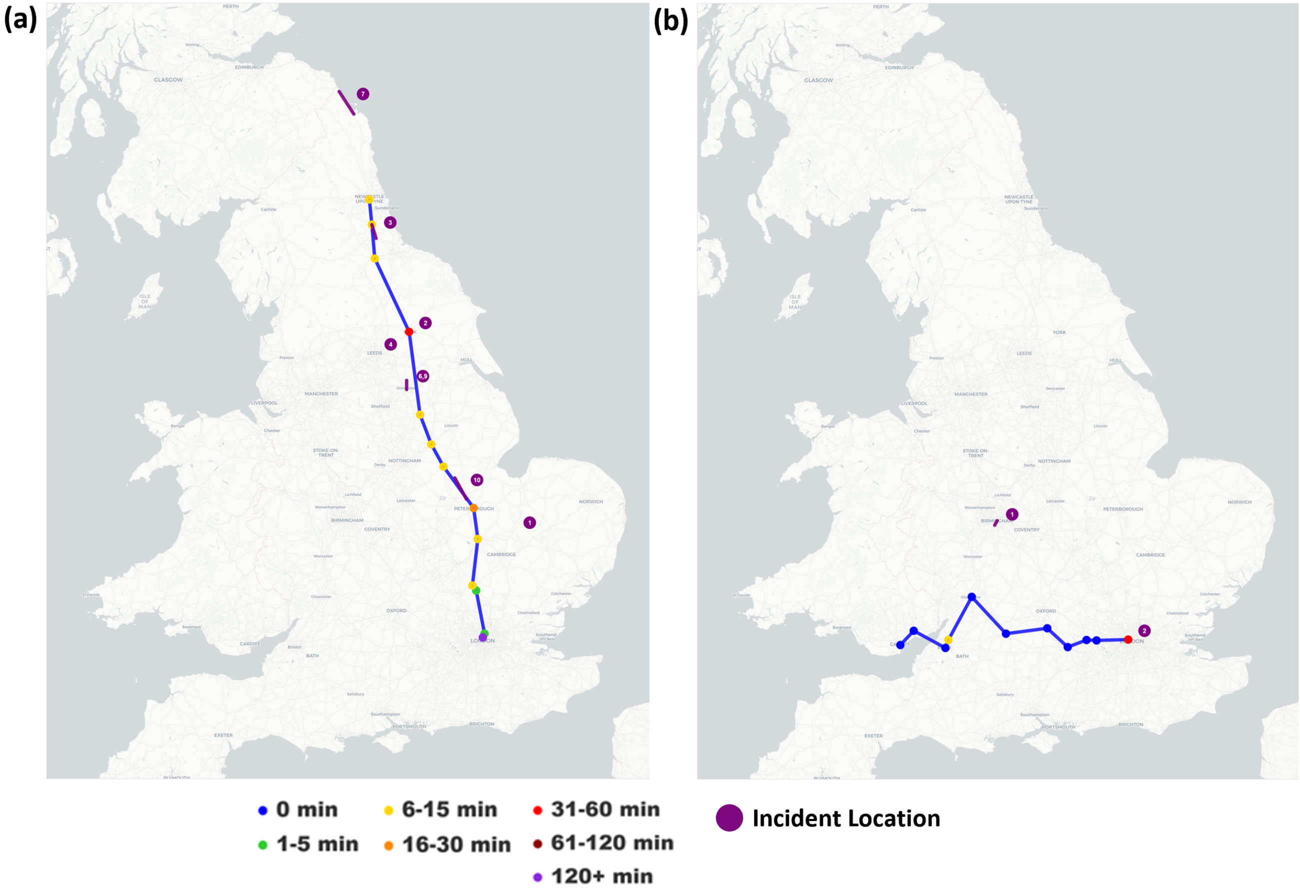

Figure 4.7: *Train View* illustrating the impacts caused by all incidents in one specific day for one specific service: 21700001 on 7th December 2024 in (**a**) and 25375002 on 9th November 2024 in (**b**).

4.6 Time View

4.6.1 Module Description

The *Time View* module provides network-wide performance for a selected date presents all incidents that occurred within that day. Unlike other views that focus on individual incidents or trains, this module summarizes cumulative impacts of all disruptions. In this view, disruptions are represented on a station-by-station basis, where the record for each station includes the number of incidents affecting it and the total delay minutes accumulated over day. The classification of delay severity is consistent with that used in the *Aggregate View* and *Incident View*.

4.6.2 Case Study

For illustration, Figure 4.8 compares two days: 31 January 2024 and 28 April 2024. In the figure, affected stations are indicated by circular markers, whose colour and size respectively indicate the severity of cumulative delay minutes and the number of incidents involved. In the case of 31 January in Figure 4.8(**a**), station markers remain small and mostly display low-severity colours from green to yellow. In contrast, the 28 April case in Figure 4.8(**b**) exhibits larger station markers with extensive high-severity colouring, mostly from red to purple, reflecting widespread disruptions with high severity throughout the day. This day also experienced a much wider spread of disruptions.

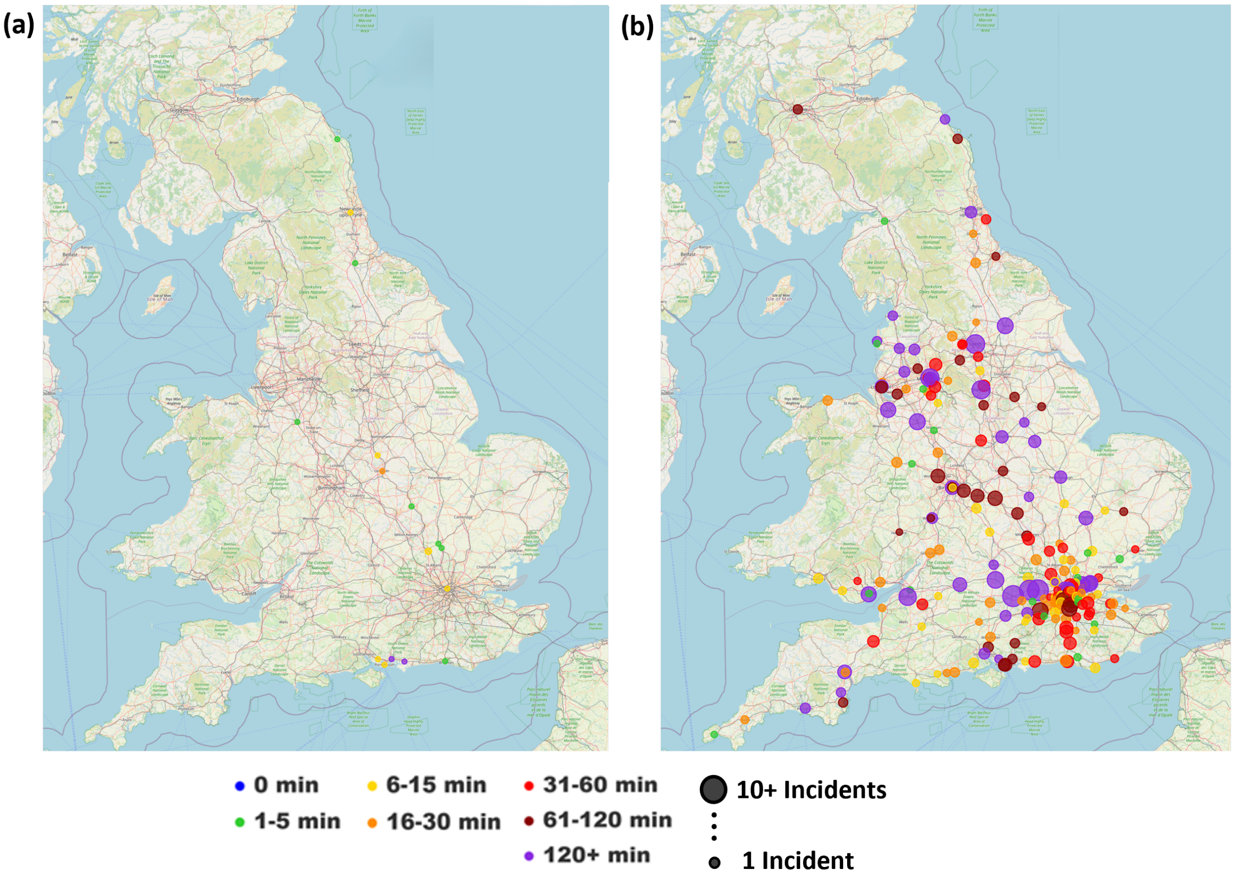

Figure 4.8: *Time View* illustrating the impacts caused by all incidents in one specific day: (**a**) 31 January 2024 and (**b**) 28 April 2024. Each circle represents a station, with its colour showing severity and its size indicating the number of incidents.

5. Discussion

5.1 Structural Patterns and Variability in Station Performance

Magnitude of delays and occurrence of cancellations generally show a positive correlation with train loadings, as evidenced in Figures 4.1**a**-**b** and 4.2**a**-**b**. Despite the structural patterns, there is high variance in delay occurrences, as indicated by the high dispersion of data points in Figures 4.1**a**-**b** and 4.2**a**-**b**. Such variances imply epistemic uncertainty arising from conditions outwith the proposed analysis modules, as well as aleatory uncertainty owing to the inherently stochastic nature of operational conditions.

Stations show a varying capacity, i.e. tph per platform, as analysed in Section 4.2.2. While the underlying factors are outside of the scope of the current work, station performance may be influenced by infrastructure characteristics such as platform availability and configuration, track layout, degree of modernization, and staff expertise. For example, the mix of bay and terminating platforms can influence how effectively a station digests the same level of train demand. Stations with more terminating platforms may see their bay platforms saturate more quickly as through-service volumes increase. Track design could be an additional factor, as trains with more carriages may experience delays in navigating station's track layouts not optimised for high-capacity services. Newer stations, by contrast, may incorporate these considerations in their design, enabling high-demand operations while maintaining relatively low delays. Staffing effectiveness, particularly in crowd management and operational coordination, may further condition observed performance outcomes. Taken together, these interpretations suggest the presence of latent structural and organisational drivers that warrant further investigation.

5.2 Timetabling Constraints and Topological Capacity in Demand Accommodation

In addition to station-level infrastructure, demand accommodation may be constrained by timetabling structure and effective topological capacity. Timetables define service sequences through fixed headways, dwell times, and recovery margins, which influence operational flexibility under elevated demand. As capacity utilisation increases, available slack is reduced, increasing sensitivity even to small delays.

Network topology further conditions how timetable constraints manifest, as the spatial arrangement of routes, junctions, and service interactions determines where competing flows converge. Stations and links at central locations may experience higher effective load, particularly where timetable rigidity coincides with high demand intensity. Under such conditions, capacity constraints may manifest through the accumulation of delays on specific services, in some cases culminating in cancellations, or through short-turning strategies where on-time services terminate upstream of their scheduled destination.

5.3 Influence of Incident Preparedness on Network-Wide Disruption Mitigation

Incident preparedness influences the evolution of network disruptions. For example, the weather-related incident in Figure 4.4**c**-**d** has its start time at 00:01 indicate that these events was likely known in advance. In this case, delay magnitudes remained relatively limited, suggesting that early mitigation measures were in place. However, as the weather event persisted, it is observed that delays increased in magnitude and became more spatially widespread, coinciding with the occurrence of additional related incidents. These secondary disruptions would be associated with operational and personnel-related mechanisms, such as reduced visibility caused by debris or leaves on windscreens and staffing constraints arising during the event. Another example are planned incidents (cf. Figure 4.5**e**-**f**), which include scheduled works and routine inspections. Impacts of these incidents also tend to remain localized and mild.

This observation highlights the importance of *a priori* planning in preventing cascading operational incidents during extended events. Such advance planning also has implications for abrupt incidents, as their impacts would be mitigated similarly through effective protocols already in place.

5.4 Implications for Future Data Collection and Integration

Based on the outcomes of this study, this section recommends avenues for improving future data collection and integration. Station and asset linkage is often mediated through multiple operational identifiers, including CRS, STANOX, and TIPLOC codes, each reflecting distinct operational functions within the network. While these identifiers are essential for operational control, their parallel use complicates data integration for research purposes, particularly where consistent spatial or functional mapping is required. The absence of a simplified, standardised linking structure increases preprocessing effort and can hinder comparative analysis across datasets, which often lacked latitude and longitude information. This points to a broader disconnect between operational data design and research usability, suggesting a need for an integrated data framework designed to support across operational and research domains.

Further challenges arise from the presence of inconsistently defined terminology, where similar data may be recorded under different labels or reported at varying levels of aggregation. Some variables use ambiguous terminology that is poorly explained in their metadata. This calls for a renewal of existing terminology systems, or more broadly the development of ontology-based frameworks, to consistently represent and integrate a comprehensive range of concepts, relationships, and data objects.

Finally, to support research on predictive simulation models, integration of qualitative information with quantitative incident records can provide invaluable understanding by providing contextual detail on incident circumstances, operational constraints, and response conditions, which cannot be captured in structured fields. While NWR Environmental Incidents is a valuable example that documents the occurrence and resolution of incidents, such qualitative data exists only in a very limited range. In addition, operational decision data–such as service terminations, short-turning, and re-routing decisions and decision context–in alignment with incident records would provide original insights into the complex interactions between operational decisions and network-wide delay propagations.

Once these challenges are addressed, UK rail data will represent one of the first infrastructure datasets enabling validation of simulation models for system-level performance of complex networks.

5.5 Validation & Predictive Foundations

The scope of validation undertaken in this thesis is aligned with the nature and purpose of this work as a Python toolkit. Validation was conducted through systematic Python-based unit and integration testing, ensuring that each module of the toolkit produces outputs consistent with its intended specification. The test suite, which is openly accessible alongside the source code, provides a rigorous and reproducible basis for asserting that the tool behaves as designed. This form of software validation constitutes an appropriate safeguard for a toolkit at this stage of development, where the primary objective is correctness of data integration and processing rather than the evaluation of a predictive model against empirical outcomes.

It is important to clarify that this tool is, by design, a diagnostic toolkit. Its analytical capabilities are oriented towards the retrospective investigation of incidents, delays, and their propagation across the rail network, rather than towards forward-looking inference. The tool enables users to interrogate any incident or operational event across multiple analytical perspectives. This provides the user with a structured and flexible means of understanding the behaviour of the network under varying conditions.

The predictive capability of this tool, while acknowledged as a natural direction for future investigation, falls outside the remit of this work. The contribution of this effort is foundational: to construct a coherent and extensible operational data tool that integrates disparate sources into a unified analytical framework. Building such a foundation is a necessary precondition for any subsequent predictive modelling effort. The prediction of delay propagation is a complex inference problem that presupposes precisely the kind of structured, high-quality dataset that this tool is designed to produce. In this sense, the present work establishes the conditions under which such focus can be meaningfully pursued.

Further confidence in the tool's behaviour is provided by the alignment of its outputs with established findings in the literature and with results from existing operational tools. As shown in Section 4.2, the station view module characterises the performance of station assets across the full temporal extent of the provided dataset. The patterns observed through this module are consistent with those reported in comparable research efforts and operational assessments. This alignment offers an initial and meaningful indication that this tool produces outputs that reflect operational conditions. While a formal comparative validation remains a valuable direction for future work, the consistency of these findings with external evidence supports confidence in the tool's diagnostic integrity at this stage of development.

5.6 Limitations and Future Research

While providing original insights to network-level rail disruptions, the scope of this study is not exhaustive. As referenced in Section 5.5, future work is essential for the investigation of the tool's predictive qualities. The data here presented requires suitable quantitative validation in order to be the basis of further predictive studies. The complexity of this task was left outside of the scope of this thesis, however its fundamental nature is a noticeable immediate next step if prognostic efforts ought to be investigated.

In addition, the framework has been designed to accommodate additional layers of data, providing opportunities to expand its analytical and operational relevance. For example, rolling stock information could be included to provide more accurate data on the network usage. The framework can also integrate environmental data such as weather conditions, which will allow examination of both direct and indirect impacts on network performance of adverse environments. Detailed station platform data, such as platform type (through, bay, or terminating), platform length, and track allocation, can be linked to train movements to improve assessment of station processing capacity and potential bottlenecks. Carriage-level information for each service should be included to better understand train length, capacity, and its interaction with platform infrastructure, particularly in relation to congestion and train motion. Similarly, passenger capacity data can be integrated to facilitate analysis of overcrowding, passenger redistribution during disruptions, and the operational implications for service recovery. Incorporating these layers would substantially expand the tool's explanatory and predictive capabilities. Furthermore, the integration of very short-term planning data represents a particularly valuable extension, as it would allow the framework to determine whether operational teams were aware of an incident in advance and were deliberately introducing measures such as pre-emptive delays for resilience purposes. This would help disambiguate reactive from proactive operational responses, strengthening the interpretability of the assumptions made during the analysis of disruption dynamics, such as those discussed in Section 5.3.

These results underscore the importance of multi-level analysis in interpreting system performance. They demonstrate that observed patterns may be influenced by latent or unmeasured conditions, highlighting opportunities for deeper investigation into causal mechanisms and underlying sources and structures of uncertainty. Beyond day-specific observations, situating performance within a broader historical context enables comparison with longer-term operational behaviour, revealing recurrent delays and identifying stations or network segments that disproportionately influence journey outcomes. By embedding local observations within the wider network context, this perspective can support a more comprehensive understanding of service reliability and the interactions that shape network resilience and capacity under operational stress. Moreover, linking these operational impacts to passenger experience will enable effective management of passenger experience.

In addition, the tool itself would benefit from further quantitative validation. Formal uncertainty quantification represents a natural avenue for future investigation. While preliminary efforts to characterise uncertainty were undertaken during the course of this project, the epistemic uncertainty arising from incomplete or inconsistent data sources, combined with the aleatory uncertainty inherent to the stochastic nature of railway operations, rendered classical quantification metrics insufficient to produce an interpretable picture at this stage. The complexity and variability of the data landscape precluded robust conclusions from these initial attempts. As the framework matures and additional data layers are incorporated, reducing epistemic uncertainty in particular, formal uncertainty quantification becomes a natural and well-motivated next step, with the potential to meaningfully strengthen the analytical rigour of future iterations of this work.

Validation through practical usage is another dimension worth pursuing. This could include a thorough assessment of interface usability, a critical element in establishing user accessibility and satisfaction. By focusing on how the tool is actually used, users are better supported and feedback can be actively encouraged. As mentioned in Section 5.6, adding layers of data would expand the tool's capabilities, but this is only possible if users are practically engaging with and contributing to the platform, something that depends on the tool being accessible, productive, and intuitive. Further attention to this aspect would reinforce the success of the tool and, in turn, deepen the understanding of UK railway network dynamics.

6. Concluding Remarks

This study proposes a data analytics framework to investigate delay propagation in the UK rail network, with a particular focus on understanding the disruption propagation dynamics at the network-level. This approach outputs operational insights able to support effective decision-making for rail disruption management. To achieve this, the framework maps operational railway datasets, namely incident and schedule data sourced from the Rail Data Marketplace (RDM) database, and thereby reconstructs the past disruption events from the occurrence of a local incident to the subsequent nation-wide propagation of delays.

The framework provides five complementary analytical modules, each designed to examine disruptions from a distinct perspective. These modules, Station View, Incident View, Aggregate View, Train View, and Time View, are mutually supportive and together provide a coherent picture of network behaviour. Each module captures different facets of the railway system, allowing both temporal and spatial aspects of disruptions to be isolated and analysed. Their combined use enables stakeholders to interpret network dynamics at multiple scales, from individual stations and trains to the entire system.

The Station View focuses on evaluating the performance of individual stations under varying traffic loadings, examining the relationship between train flow and accumulated delays at a chosen station. This view provides station-level insights into both general patterns of station vulnerability and differences in performance across stations. In contrast, the Incident View provides a detailed geographical mapping of how a local incident leads to cascading disruptions across the network over time. The Aggregate View offers a high-level perspective on how a single incident can influence network-wide operations over time. It provides a general impact view of delay minutes and cancellations during one incident. The Train View follows the journey of a selected train service, mapping the stations affected by delays and the incidents responsible for them. Finally, the Time View produces a spatial report that summarises a full day's incidents and delays across all stations.

The application of this framework to the UK rail network revealed several key observations. For example, certain stations and routes were consistently identified as highly vulnerable to the propagation of delays. This observation highlights critical locations where targeted interventions could mitigate delay propagation. Temporal analysis demonstrated periods of heightened susceptibility, often linked to dense service schedules. This suggests opportunities in the improvement of timetable schedules or targeted resource allocation to absorb this demand. In addition, it demonstrates that incident reason and incident location generate a different impact propagation across service routes.

Together, these modules form a dashboard that enables understanding of how localised incidents can cascade into network-wide impacts, supporting operational assessment and strategic planning for disruption mitigation. While the framework has the potential to inform practical decision-making in the longer term, its immediate purpose is to generate research data for the data-validated simulation and optimisation of rail disruption propagation. Thereby, it is envisioned to contribute to technological developments that support more reliable rail services both in the UK and worldwide.

While this work has demonstrated the utility of a data-driven approach, there remain several avenues for future research. Recognising the need for further research on rail disruption management, the framework has been deliberately designed to facilitate adoption and further extensions. The framework could be expanded to include additional data layers, such as freight operations, passenger loadings, or weather conditions. These layers would allow for a more holistic understanding of network performance under varying operational and environmental conditions. Further developments could also focus on predictive applications using operational data. Probabilistic models could support the identification of patterns to anticipate future disruptions and inform decision-making. Ultimately, translating these insights into actionable guidance for network operators and stakeholders could contribute to a more resilient, efficient, and sustainable UK rail system.

A. Supplementary Materials

A.1 Raw Datafiles Examples and Structure

Table A.1: Raw NWR Historic Delay Attribution Example for Appendix

NWR Historic Delay Attribution	
FINANCIAL_YEAR_PERIOD	2023/24_P12
ORIGIN_DEPARTURE_DATE	04-FEB-24
TRUST_TRAIN_ID	011A48MF04
PLANNED_ORIGIN_LOCATION_CODE	01100
PLANNED_ORIGIN_WTT_DATETIME	04-FEB-2024 09:59
PLANNED_ORIGIN_GBTT_DATETIME	04-FEB-2024 09:59
PLANNED_DEST_LOCATION_CODE	02071
PLANNED_DEST_WTT_DATETIME	04-FEB-2024 12:15
PLANNED_DEST_GBTT_DATETIME	04-FEB-2024 12:15
TRAIN_SERVICE_CODE	23547003
SERVICE_GROUP_CODE	HA04
TOC_CODE	HA
ENGLISH_DAY_TYPE	SU
APPLICABLE_TIMETABLE_FLAG	Y
TRAIN_SCHEDULE_TYPE	LTP
TRACTION_TYPE	DME
TRAILING_LOAD	
TIMING_LOAD	E
UNIT_CLASS	
INCIDENT_NUMBER	135907
INCIDENT_CREATE_DATE	29-DEC-2023 00:00
INCIDENT_START_DATETIME	29-DEC-2023 04:23
INCIDENT_END_DATETIME	31-DEC-2023 12:37

NWR Historic Delay Attribution (continued)	
SECTION_CODE	02042:02031
NR_LOCATION_MANAGER	OQL0
RESPONSIBLE_MANAGER	XQLT
INCIDENT_REASON	X2
ATTRIBUTION_STATUS	Attribution Agreed
INCIDENT_EQUIPMENT	SCR8304A
INCIDENT_DESCRIPTION	DYC KTR 40MPH ESR D/L SCR8304A
REACT_REASON	YE
INCIDENT_RESP_TRAIN	
RESP_TRAIN	
REACT_TRAIN	021H27MG04
EVENT_TYPE	M
START_STANOX	02015
END_STANOX	02029
EVENT_DATETIME	04-FEB-2024 11:42
PFPI_MINUTES	4
NON_PFPI_MINUTES	0

Table A.2: Raw Schedule File Example (CIF Format)

Train Schedule Metadata	
CIF_bank_holiday_running	null
CIF_stp_indicator	P
CIF_train_uid	C00132
applicable_timetable	Y
atoc_code	HX
schedule_days_runs	0000001
schedule_start_date	2025-05-18
schedule_end_date	2025-12-07
train_status	P
transaction_type	Create
New Schedule Segment	
traction_class	
uic_code	

Train Schedule Metadata (continued)	
Schedule Segment	
signalling_id	1T95
CIF_train_category	XX
CIF_headcode	0101
CIF_course_indicator	1
CIF_train_service_code	25905000
CIF_business_sector	null
CIF_power_type	EMU
CIF_timing_load	387
CIF_speed	110
CIF_operating_characteristics	D
CIF_train_class	null
CIF_sleepers	null
CIF_reservations	S
CIF_connection_indicator	null
CIF_catering_code	null
CIF_service_branding	null
Schedule Location Example (LO)	
location_type	LO
record_identity	LO
tiploc_code	PADTON
departure	2257
public_departure	2255
platform	6
line	3
engineering_allowance	null
pathing_allowance	null
performance_allowance	null
Schedule Location Example (LI)	
location_type	LI
tiploc_code	ROYAOJN
pass	2258
line	4
Schedule Location Example (LT)	
location_type	LT

Train Schedule Metadata (continued)	
tiploc_code	HTRWTM5
arrival	2320
public_arrival	2320
platform	4

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