System Level Reliability Modelling and Analysis of a Container Terminal

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MSc Thesis

TU Delft

System Level Reliability Modelling and Analysis of a Container Terminal

by

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Summary

This thesis presents a system-level reliability modelling framework for analyzing how failures, maintenance activities, and operational disruptions spread through interconnected subsystems in container terminal operations. The research combines reliability analysis with probabilistic reasoning to provide a clear understanding of how technical, human, and environmental factors affect delays and system performance. This connection is established by translating reliability states—such as equipment health, availability, and maintenance effectiveness—into probabilistic delay outcomes, allowing the model to quantify how reliability losses lead to operational delays.

The framework integrates Fault Tree Analysis (FTA) and Bayesian Networks (BNs) to capture both causal and probabilistic relationships within the terminal system. FTA decomposes the top event—total operational delay—into its contributing factors, providing the structural foundation for the BN. The initial BN structure captures subsystem interactions through nodes representing equipment failure, availability, efficiency, and environmental conditions. Each node describes a key aspect of terminal performance. Equipment failure indicates the operational state of critical assets and is modelled with a Weibull distribution. Availability represents the percentage of time each subsystem could work. Efficiency reflects performance under different external or internal constraints. Environmental factors, yard storage fullness, and terminal busyness acted as external drivers that influenced subsystem efficiency and delay propagation.

The BN model was further expanded to include maintenance and operator availability as new influencing factors. Both preventive and corrective maintenance were considered within the model. The maintenance effectiveness was determined using Weibull-based reliability parameters. The scale and shape parameters were adjusted through maintenance effect multipliers to account for imperfect repair conditions. This method enabled the BN to show how preventive maintenance improves equipment availability. Operator availability was also considered to account for human-related variability, showing how workforce presence impacts subsystem operability and overall delays.

The analysis of the BN used forward inference and sensitivity testing. The results indicate that disruptions in one subsystem can spread through the terminal, causing cumulative delays and underscoring the strong interconnections between quay cranes, yard cranes, and horizontal transport. The maintenance analysis revealed that by implementing preventive maintenance strategies, equipment availability could be increased. Operator availability affected total delay mainly during severe disruptions like strikes, while daily variations had a limited impact.

This developed framework combines reliability modelling and operational performance analysis in one structure. It offers a clear way to study how maintenance, operator availability, and environmental conditions influence reliability and delay in terminal operations. While the framework was created for container terminals, the same approach could be adapted to other connected systems where equipment, people, and external conditions interact to affect overall performance.

Ece Coksayar
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List of Abbreviations

Abbreviation	Definition
AGV	Automated Guided Vehicle
BN	Bayesian Network
CBM	Condition-Based Maintenance
CPT	Conditional Probability Table
DBN	Dynamic Bayesian Network
FTA	Fault Tree Analysis
HT	Horizontal Transport
KNMI	Royal Netherlands Meteorological Institute
MHC	Mobile Harbour Crane
MTBF	Mean Time Between Failures
MTTR	Mean Time to Repair
PM	Preventive Maintenance
QC	Quay Crane
RBD	Reliability Block Diagram
RMG	Rail-Mounted Gantry Crane
RTG	Rubber-Tyred Gantry Crane
STS	Ship-to-Shore (Crane)
TE	Top Event (in FTA)
TT	Terminal Tractor
YC	Yard Crane

1 Introduction

Reliability is a key concern in complex industrial systems, reflecting their ability to perform their intended functions under specified conditions for a given period (Doguc & Ramirez-Marquez, 2009; Nakagawa, 2005; Rausand & Høyland, 2004). It serves as a key indicator of system quality and robustness, ensuring safe, efficient, and cost-effective operations. High reliability minimizes downtime, stabilizes output, and can lower maintenance costs (L. Zhao et al., 2023). In large-scale operational systems such as container terminals, even minor reliability losses can disrupt interdependent processes. These disruptions can create bottlenecks, delay vessel turnaround and increase logistics costs. Therefore, it is crucial to understand the main technical and operational factors impacting the system's reliability and performance, and how to improve on them.

Reliability assessment traditionally relies on structured techniques like Failure Mode and Effects Analysis (FMEA), Fault Tree Analysis (FTA), and Reliability Block Diagrams (RBD) (Friederich & Lazarova-Molnar, 2024; Rausand & Høyland, 2004). These methods provide systematic ways to spot potential failure modes and assess their impact on system performance. FMEA evaluates risk based on the likelihood of failure, its severity, and how easily it can be detected (Alyami et al., 2014; Nguyen et al., 2019). RBDs represent systems as components arranged in series or parallel to calculate overall reliability (Friederich & Lazarova-Molnar, 2024; Lv et al., 2010). FTA uses logical relationships to map out combinations of basic events that lead to system failure (X. Luo et al., 2024). Even though these methods are useful, they mainly focus on component-level reliability and generally assume binary operating states: fully functional or failed (Animah, 2024). This simplification makes analysis more straightforward but limits the ability to represent interdependencies, shared failure causes, and gradual degradation. In real industrial operations, systems are dynamic and interconnected. A partial loss of performance or reduced capacity in one subsystem can affect others through shared resources or process connections (N. Wang et al., 2023; L. Zhao et al., 2023). Such degradations often do not cause total failure but instead lead to delays that accumulate and propagate across the system. As a result, traditional reliability methods are effective at estimating the likelihood of failure but not its operational consequences in time-based performance terms, which are essential for understanding system-level efficiency and delay behavior.

To represent these dynamic relationships, researchers have explored probabilistic and simulation-based approaches that capture dependencies and uncertainty. Bayesian Networks (BNs) have gained attention in reliability engineering for their ability to model probabilistic dependencies among components and failure events (Langseth & Portinale, 2007). They improve on traditional methods by incorporating conditional relationships and allowing reasoning under uncertainty. However, most BN applications still focus on component reliability, estimating failure probabilities or availability without linking these states to operational performance.

Likewise, discrete-event and agent-based simulations can reproduce how reliability losses, congestion, and operational disruptions propagate through a system with high realism. Yet, these methods require extensive data and computational effort, making them less suitable for rapid scenario evaluation or early-stage analysis. As a result, they provide limited ability to capture how reliability degradation affects system performance over time, particularly in terms of delay propagation.

Understanding this connection between reliability and delay is especially important in container terminal operations, where multiple subsystems—such as quay cranes, yard cranes, and horizontal transport—are tightly interdependent. Technical reliability, maintenance effectiveness, workforce availability, and environmental conditions all contribute to performance variation and delay propagation. Although simulation studies provide detailed representations of terminal operations, integrating reliability, maintenance, and delay propagation within a single modelling framework remains a complex task.

1.1. Research Questions

The objective of this research is to develop a structured approach to system reliability modelling, integrating analysis methods to enhance decision-making in complex operations. The main research question is *"How can system reliability be assessed and improved in dynamic operational environments where performance depends on interacting technical, human, and environmental factors?"*. The subquestions are as follows:

- How can reliability be modeled beyond component failures to capture interdependencies, degradation, and operational disruptions at the system level?
- How can system-level analysis be used to evaluate the impact of maintenance, operator availability, terminal situation, and environmental factors on overall reliability and operational performance?

The remainder of this thesis is organized as follows. Chapter 2 reviews the theoretical background of reliability engineering and summarizes the relevant literature on system-level reliability modelling, simulation studies in the container terminal context, and application of BNs within delay propagation and container terminals. Chapter 3 describes the methodology, outlining the development of the proposed reliability framework. Chapter 4 focuses on the system description, detailing the system structure and maintenance strategies applied. Chapter 5 explains how the BN is structured and how the equipment health is modelled. Chapter 6 discusses the results of the analysis, including how maintenance, operator, and environmental factors influence reliability and operational performance and the delays propagate within the system. Chapter 7 presents a discussion of the results, strengths, and limitations of the model. Finally, Chapter 8 concludes the thesis by summarizing the key findings and suggesting directions for future research.

2

Literature Analysis

Reliability analysis is essential for ensuring the consistent performance of complex systems. Over time, various methods have been developed to model system failures, assess risks, and improve operational efficiency. System reliability modelling approaches such as Reliability Block Diagrams (RBD), Fault Tree Analysis (FTA), and Failure Mode and Effects Analysis (FMEA), provide structured ways to evaluate component reliability and system failure logic. However, they typically treat systems as static and binary. With the increasing interconnection and data availability in modern operations, reliability modelling has evolved toward probabilistic and data-driven techniques that can represent dependencies and uncertainty. Among these, Bayesian Networks (BNs) have gained prominence for combining causal structure with probabilistic inference, enabling updates from both expert judgment and data.

Parallel to these advances, discrete-event and agent-based simulations have become the dominant tools for studying how reliability losses, congestion, and operational interactions affect performance. While simulation offers high realism, it is computationally intensive and often impractical for extensive scenario exploration or early-stage analysis.

Beyond reliability assessment, BNs have also been used to study delay propagation in complex systems such as aviation, rail, and public transport networks, where they capture how local disruptions cascade through interdependent processes and affect overall performance. In the context of container terminals, existing research has applied BNs mainly to safety assessment, operational risk management, and resilience analysis. However, their potential to model the link between reliability and delay propagation—how equipment failures and disruptions evolve into time-based performance losses—remains underexplored.

This chapter reviews the system reliability modelling approaches and simulation approaches, examines how BNs have been applied to delay propagation and within the container-terminal context. Finally, it identifies the key research gap: the absence of an integrated probabilistic framework that connects reliability, maintenance, and delay propagation within a single system-level model.

2.1. System Reliability Modelling Approaches

Reliability assessment has traditionally relied on structured modelling techniques that aim to quantify failure risks and system performance. These methods typically represent a system as a combination of individual components and their interactions. Three widely used techniques in system reliability analysis are Reliability Block Diagrams (RBD), Fault Tree Analysis (FTA), and Bayesian Networks (BN). RBD provides a graphical method for modelling system reliability based on series and parallel configurations, helping to calculate overall system reliability. FTA is used for deductive failure analysis, enabling engineers to visualize failure pathways and determine the most critical failure events. BN extends traditional methods by introducing probabilistic reasoning, allowing systems to dynamically update failure probabilities based on observed conditions.

2.1.1. Reliability Block Diagram

The interconnection of components within a system can be represented using a RBD. Each block represents a subsystem, and the overall system reliability depends on how these blocks are arranged and interact. In an RBD, components are either arranged in series, or in a parallel configuration. In a series configuration, all components must function correctly for the system to operate, as failure of a single component leads to system failure. With parallel configuration, redundancy is introduced, meaning that the system is operable as long as at least one component in the parallel block remains operational. An RBD schematic can be found in Figure 2.1.

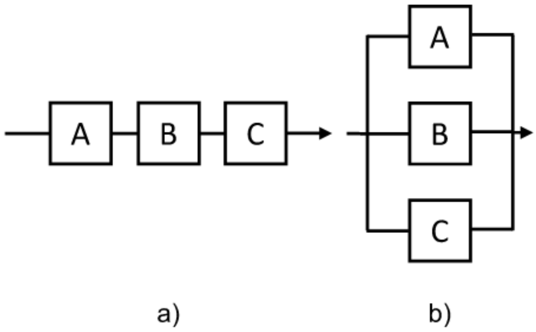


Figure 2.1: RBD with system in sequential (a) and parallel (b) configuration (Friederich & Lazarova-Molnar, 2024)

Using an RBD, the overall reliability of a system can be computed depending on whether its components are connected in series or in parallel. According to Friederich and Lazarova-Molnar (2024), for a series of N connected components, the system reliability is defined as:

$$R(t) = \prod_{i=1}^{N} R_i(t) \tag{2.1}$$

For N parallel-connected components, the system reliability is defined as:

$$R(t) = 1 - \prod_{i=1}^{N} (1 - R_i(t)) \tag{2.2}$$

In practice, RBDs are widely used in industries where redundancy and system architecture play a crucial role in ensuring safety and performance. Manufacturing and process industries apply RBDs to identify bottlenecks in production lines and assess how component reliability affects overall system uptime (Rausand & Høyland, 2004). General applications include modelling backup generator/turbine redundancy in shipboard power systems (Van Der Sande et al., 2025) and parallel feeder–transformer configurations in industrial power distribution (*IEEE Recommended Practice for the Design of Reliable Industrial and Commercial Power Systems (Gold Book)*, 2007). These applications demonstrate that RBDs are a versatile and intuitive tool for quantifying system reliability and optimizing design configurations before implementation. However, RBDs assume binary up/down behavior and independent components, so they do not capture common-cause failures, load sharing, state- or sequence-dependent behavior, repair/maintenance dynamics, queues and congestion, or multi-state performance levels (J. Zhao et al., 2017).

2.1.2. Fault Tree Analysis

Within reliability engineering, FTA is used to analyse and predict the failure behaviour of systems and processes (Friederich and Lazarova-Molnar, 2024). This method employs a graphical representation known as a fault tree to illustrate the potential causes of a system failure. A fault tree is a diagram that depicts the various combinations of events or conditions that can lead to the occurrence of an undesired event, and it can be visualized in Figure 2.2.

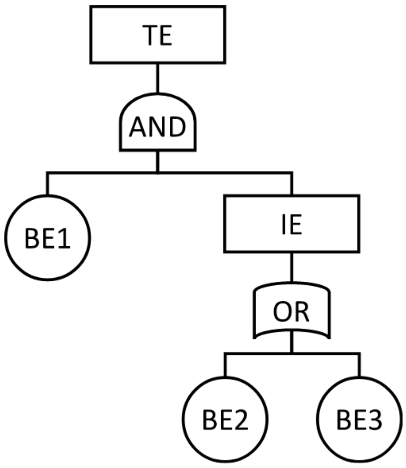


Figure 2.2: Fault tree with top (TE), intermediate (IE) and basic events (BE) (Friederich & Lazarova-Molnar, 2024)

This method models an undesired top event and decomposes it into combinations of basic events using logic gates such as AND/OR, k-out-of-N, to explain how failures propagate and to support qualitative and quantitative assessment (Friederich & Lazarova-Molnar, 2024). In practice, FTA is used in many industries, including power generation, process engineering, aerospace, and information technology, to identify critical failure combinations and estimate the risk of system outages (Ruijters & Stoelinga, 2015). However, static FTA assumes binary and independent events. As a result, the method requires specific extensions to capture effects such as event ordering, maintenance and repair dynamics, load sharing, multi-state behaviour, and common-cause failures (Ruijters & Stoelinga, 2015; J. Zhao et al., 2017).

2.1.3. Bayesian Networks

In reliability engineering, a BN provides a probabilistic framework for representing and reasoning under uncertainty in complex systems. The network consists of a directed acyclic graph (DAG) and a probabilistic model that defines dependencies between variables, and it has been widely used in reliability analysis (Friederich & Lazarova-Molnar, 2024; H. Wang et al., 2019). One of its main strengths is the ability to capture dependencies among system components and potential failure sources (Langseth & Portinale, 2007). This approach allows representation of relationships between failures, such as common causes and standby redundancies (Torres-Toledano & Sucar, 1998).

In a BN, nodes represent variables, while edges define conditional dependencies between them. Each node is associated with a conditional probability table (CPT), which quantifies the probability of the node's state given the states of its parent nodes. These CPTs are typically used for discrete variables and are initially derived from prior knowledge or empirical data. For continuous variables, conditional probability distributions—such as normal or Poisson distributions—can be used instead. In both cases, the network can be updated based on new observations using Bayes' rule (Friederich and Lazarova-Molnar, 2024).

When building a BN, FTA can serve as a structured foundation for systematically mapping fault relationships into probabilistic dependencies. Since FTA represents system failures using logical gates (e.g., AND, OR) to define how component failures contribute to system failure, these gates can be directly translated into BN fragments with binary nodes, where each node represents a failure state (X. Luo et al., 2024). A visualization of constructing a BN using an FTA can be found in Figure 2.3.

For more complex systems, subsystems can be modeled independently and then integrated into a larger network. This modular construction makes BNs particularly effective for large-scale systems, where failure dependencies extend across multiple interconnected subsystems (Rigdon, 2008). Figure 2.4 shows an example of a BN representing a bridge-type system, where different paths between components A–E can lead to system success. Rather than analysing all possible combinations manually, intermediate nodes (S1–S4) represent logical groupings of components, simplifying the structure and facilitating the calculation of overall system reliability. The final node (P) denotes the overall system state.

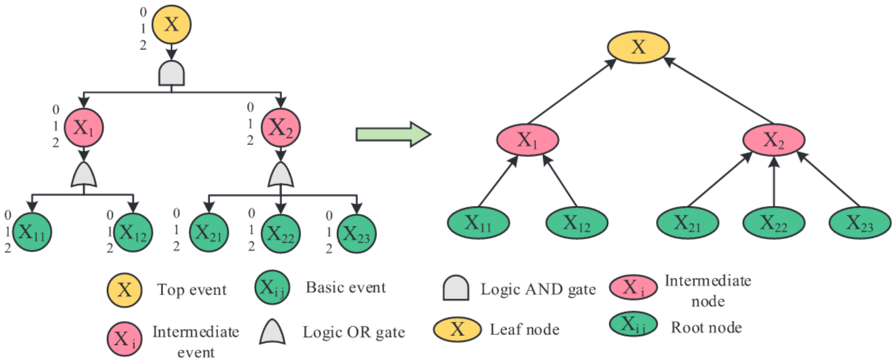


Figure 2.3: FTA to BN visualization

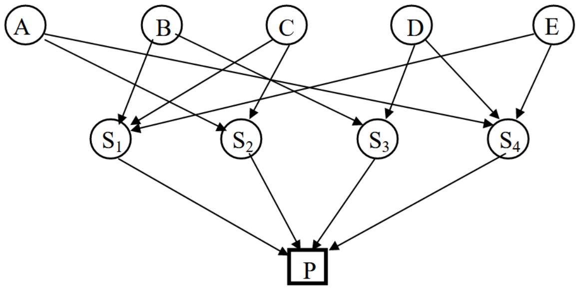


Figure 2.4: Bayesian Network visualization of a complex system (Torres-Toledano & Sucar, 1998)

In reliability applications, BNs are used to combine expert judgement and empirical data for diagnosis, prognosis, and decision support across domains such as power and process industries, transportation systems, and condition-based maintenance. They are particularly useful when common causes, shared environments, or standby dependencies are present (Friederich & Lazarova-Molnar, 2024; Langseth & Portinale, 2007; H. Wang et al., 2019). The approach effectively captures dependency structures, updates risk with new observations, supports modular modelling of large systems, and integrates FTA-derived logic as BN fragments for probabilistic reasoning (X. Luo et al., 2024; Rigdon, 2008; Torres-Toledano & Sucar, 1998).

2.2. Container Terminal Simulation Studies

Simulation modelling is one of the most established approaches for analysing and improving container terminal operations in both academic research and industrial practice. In particular, discrete-event simulation (DES) and agent-based modelling (ABM) dominate the field, as they can represent vessel movements, container transfers, crane operations, and yard processes in detail (Carlo et al., 2014; Dragović et al., 2017; Vis & De Koster, 2003).

In DES, terminal activities are modelled as a sequence of discrete events—such as ship berthing, crane movements, and truck arrivals—each occurring at a specific time. The method is widely used to analyse throughput, resource utilisation, queuing, and congestion, providing insights into how process-level variations affect overall terminal performance. DES has been applied to a wide range of problems, including berth allocation and quay-crane productivity (Legato & Mazza, 2001), capacity planning and operational strategies (Cartenì & Luca, 2012; Elentably, 2016), and predictive estimation of vessel operation times under stochastic conditions (Park et al., 2024). More recent work combines DES with reliability modelling to capture how equipment failures and maintenance influence performance and resilience (Rosca et al., 2025).

Agent-based modelling represents the terminal as a system of autonomous entities—such as cranes, yard vehicles, and operators—that follow behavioural rules and interact dynamically with one another and their environment. This approach is particularly suited to capture coordination, decision-making, and information exchange in complex terminal operations. ABM has been applied to model scheduling and resource sharing among cranes and transport vehicles (Li & Li, 2010), to analyse coordination and negotiation strategies in yard operations (Winikoff et al., 2011), and to explore multimodal interactions between ships, barges, trains, and trucks (Mazloumi & Van Hassel, 2021). Across these applications, ABM offers flexibility for testing operational policies, evaluating collaboration between subsystems, and assessing how local interactions and adaptive behaviours affect overall terminal efficiency.

Within simulation-based research, delay is often used as a central indicator of terminal performance. Delays typically arise from a combination of congestion, limited resources, and coordination issues between terminal subsystems. Studies such as Dragović et al. (2017), Yang et al. (2004), and Park et al. (2024) demonstrate that simulation models can effectively visualise how localised disruptions—such as crane interference, vehicle queues, or yard congestion—propagate through interconnected operations and extend vessel turnaround times. Broader simulation analyses, including Srisurin et al. (2022) and Cartenì and Luca (2012), further show that discrete-event frameworks are capable of assessing long-term capacity and congestion under varying infrastructure or policy scenarios.

While simulation models provide valuable insights into terminal operations, they generally focus on operational efficiency rather than underlying reliability effects. Most studies analyse how congestion, resource allocation, or scheduling decisions create delays but pay less attention to how reliability-related factors influence these outcomes.

2.3. Delay Propagation using Bayesian Networks

Delays are a critical factor in system performance and have a direct impact on operational efficiency across industrial systems. In interconnected systems, a delay at one stage can trigger future disruptions in the system. A BN provides a probabilistic framework for modelling delay propagation by representing how disruptions at one stage influence other parts of the system. This approach captures causal dependencies between events, allowing for a more realistic representation of system-wide delay effects while incorporating uncertainty.

Research on delay propagation using BNs has been applied in aviation systems to predict cascading flight delays (Y.-J. Liu and Ma, 2008; Xu et al., n.d.), in rail transit networks to identify patterns of systemic inefficiencies (Ulak et al., 2020), and in passenger transport systems (Cats and Hijner, 2021) to quantify the cascading effects of disruptions. However, while BN models have proven useful for analysing delay propagation, existing research often treats delays separately from system reliability, without fully integrating them into broader reliability optimisation frameworks.

Delays can be generally categorized into primary (root cause) delays and secondary (propagated) delays (Ulak et al., 2020). Primary delays are initial disruptions caused by specific events such as equipment failures, weather conditions, or operational inefficiencies. Mechanical failures in trains or aircraft (Ulak et al., 2020) and airport congestion affecting on-time departures (Y.-J. Liu and Ma, 2008) can be given as examples of primary delays. Secondary Delays (Knock-On Delays) occur when an initial delay affects other parts of the system. For example, a delayed flight causes missed passenger connections, leading to further delays in the network (Wu and Law, 2019), and a train arriving late at a transfer station leads to passenger delays on connecting services (Ulak et al., 2020). Categorizing delays can help in identifying delay propagation patterns.

Data for delay propagation modelling typically comes from historical records, real-time tracking systems, simulation output, and expert knowledge. Different industries collect and analyse delay data in various ways. Rail transit systems rely on real-time tracking applications, GPS logs, and scheduled vs. actual arrival times to quantify delays at different stations (Ulak et al., 2020). In aviation networks, airlines use flight operation databases that record scheduled and actual departure/arrival times to analyse delay propagation across interconnected flights (Y.-J. Liu and Ma, 2008). Similarly, public transport systems utilize smartcard transactions and vehicle GPS tracking to estimate how delays spread across the network (Cats and Hijner, 2021). These datasets help in understanding where delays originate, how they spread through the network, and which system components are most affected.

2.4. Bayesian Network Applications in Container Terminals

Within container terminal and port logistics research, BNs have been applied to capture operational dependencies and to support decision-making under uncertainty (Alyami et al., 2019; Animah, 2024; García et al., 2015; Hossain et al., 2019; N. Wang et al., 2023). Safety and Operational Risk Assessment, Resilience and Recovery Quantification, and Planning and Operational Optimisation are the main focus of existing studies.

One of the most common applications is in evaluating safety and operational risks in container terminal operating systems. Alyami et al. (2019) created one of the most detailed frameworks in this area. They combined a Fuzzy Rule-Based Bayesian Network (FRBN) with evidential reasoning to improve the traditional Failure Mode and Effects Analysis (FMEA). This hybrid FRBN-ER approach allows for realistic modelling of uncertain failure data at the component level. It supports real-time, risk-based decision-making for port operators by prioritizing hazardous events such as crane breakdowns, collisions, and dangerous goods incidents, based on their overall impact on terminal safety performance. Other studies have also used BN to model specific operational hazards. This includes vessel-berthing collisions and internal port risks related to quay crane use and vessel turnaround times (Animah, 2024).

Another research direction involves assessing and modelling the resilience of port and terminal infrastructure, focusing on the ability to maintain and restore operations after disruptions. Hossain et al. (2019) employs BN-based framework to assess the resilience of a full-service deep-water port. This study identifies how different resilience capacities, such as absorptive, adaptive, and restorative, contribute to recovery performance during challenging conditions. Their analysis showed that maintenance, alternative routing, and workforce restoration were the most influential factors in improving recovery after disruptions. Similarly, N. Wang et al. (2023) created a strategy-oriented BN model that grouped resilience factors into six key metrics: robustness, redundancy, visibility, flexibility, agility, and recovery. Their findings revealed that automated terminals had higher overall resilience compared to conventional ones.

Furthermore, BNs are applied in the container terminal context is to support strategic planning and operational optimisation within terminal management. García et al. (2015) used a BN to infer causal relationships between key port parameters—such as berth length, yard area, crane allocation, and annual container throughput (TEU)—through structural learning. The study demonstrated that BN-based models can predict how changes in infrastructure or equipment allocation impact terminal performance by simulating different operational scenarios. Additionally, Fuzzy Bayesian Networks (FBN) have been used to forecast container ship arrival times and scheduling uncertainties to help terminal operators to coordinate berth allocation and vessel handling (Animah, 2024).

2.5. Research Gaps

Reliability studies largely focus on analysing component-level failures, using methods like Fault Tree Analysis (FTA) and Reliability Block Diagrams (RBD). These approaches effectively identify failure probabilities but often overlook how those failures affect operational performance metrics such as delays or availability. On the other hand, operations research aims to optimize scheduling, resource allocation, and vessel turnaround time, typically assuming ideal or static equipment performance. Although delay propagation has been examined in broader transportation studies, these models generally treat delays as independent random events without connecting them to the underlying reliability behavior of interdependent subsystems.

Despite the increasing use of BNs in port and terminal research, current applications are still limited in scope and integration. Most studies focus on specific areas like safety management, resilience assessment, or operational planning and often treat these aspects as separate analytical domains. While these studies show that BNs can model uncertainty and causal relationships, they usually look at isolated events or steady conditions instead of the ongoing and interconnected dynamics that define real terminal operations. Consequently, the temporal and systemic nature of reliability—how equipment breakdown, maintenance activities, and external disruptions interact over time—does not receive enough attention.

This gap between reliability analysis and operational performance modelling is significant. In practice, the performance of a container terminal is influenced by technical failures, maintenance efficiency, operator behavior, and environmental factors. However, few existing frameworks bring these elements together in a single probabilistic structure that shows how disruptions affect interconnected subsystems and system-level availability and delay. While BNs offer a theoretical basis for modelling these dependencies and uncertainties, their potential for showing reliability-performance interactions in container terminals has not been fully explored. To address this gap, this research presents a system-level Bayesian Network framework aimed at modelling how failures, maintenance, and operational variability work together to influence delay propagation and overall terminal reliability.

3
Methodology

This chapter outlines the methodological framework developed to model and analyse system-level delays in complex operational environments. The approach integrates reliability analysis and probabilistic modelling to understand how failures and inefficiencies propagate across interconnected subsystems and affect overall system performance. In addition, the framework provides a foundation for exploring alternative maintenance strategies.

The methodology consists of several sequential stages. First, the system is defined in terms of its operational phases and critical components. Then, two complementary modelling tools are employed: Fault Tree Analysis (FTA) and Bayesian Networks (BNs). FTA systematically decomposes the top event, defined as the total operational delay, into its contributing failure mechanisms and intermediate events. The BN builds on this FTA logic and enables quantitative reasoning under uncertainty. The BN models dependencies between environmental conditions, equipment reliability, and delay outcomes using conditional probability distributions.

Finally, the developed BN framework is used to analyse system behaviour under different conditions. By simulating various operational scenarios, maintenance policies, and external disruptions, the model identifies key risk factors and measures their effects on overall reliability and delay propagation. While this methodology is applied in the context of a container terminal in this study, its structure is generalisable to other interdependent operational systems.

3.1. System Description

The first step in this framework is to define the system under study by identifying its critical components, disturbances, and interdependencies. This stage requires determining how components interact by mapping interfaces and coupling mechanisms. These interactions can be established via targeted literature review, on-site observations, and stakeholder interviews. One essential aspect of this stage is understanding delay propagation, which involves distinguishing between primary delays, caused by direct disruptions such as equipment failures or scheduling inefficiencies, and secondary delays, which result from cascading effects within the system, such as congestion or resource constraints. Understanding these dependencies and failure mechanisms provides the foundation for constructing the reliability model.

3.2. Reliability Model

Building a BN for system reliability and delay propagation requires defining nodes and dependencies, setting up Conditional Probability Tables (CPTs), and representing the relationships within the system. FTA is first used to systematically decompose the top event into its contributing failure mechanisms and intermediate causes. The structure derived from the FTA provides a logical basis for the BN, in which each basic failure event is represented as a node, and causal links between events define the directed dependencies within the network. In this framework, ‘delay’ represents a relative performance loss within the terminal system, modelled qualitatively in three discrete states (Low, Medium, High) rather than an absolute duration. This allows the Bayesian Network to capture uncertainty and interdependencies without requiring detailed time-series delay data.

Once the structure is established, CPTs can be created to specify the likelihood of each node's state based on the states of its parent nodes. These CPTs quantify how delays spread through the system as a result of failures, maintenance conditions, and external disturbances. In cases where historical data are incomplete, expert judgement is used to approximate probability distributions (Xu et al., n.d.).

3.3. Reliability and Delay Analysis

Once the BN model is built, it provides the basis for examining how failures, maintenance conditions, and external disruptions propagate through the system. The analysis aims to identify the factors that most strongly affect the delay behaviour and assess how operational changes, equipment reliability, or external disturbances alter system outcomes.

The analysis consists of three supporting approaches: forward inference, scenario analysis, and sensitivity analysis. Forward inference estimates the likelihood of outcomes at the system level, such as total delay or reduced availability, based on specific operational states or failure events. Scenario analysis is conducted through repeated forward inference to assess how different operational or environmental conditions impact subsystem delays and total delay. By changing the prior probabilities of input nodes, the model can simulate different operational states and compare the results. This process enables validation of the model by assessing whether the simulated outcomes align with expected operational behaviour and observed delay patterns. Sensitivity analysis identifies which factors have the greatest effect on the target variables, such as total delay or subsystem availability. The sensitivity analysis can be performed by changing the prior probabilities of selected nodes and comparing the results to a defined baseline scenario. This comparison reveals how strongly each variable influences overall system reliability and delay behaviour. By looking at these differences from the baseline, the analysis reveals the most influential factors.

4

System Description

Container terminals play a critical role in global logistics and maritime transport networks by facilitating the efficient transfer of goods between ships and inland transportation modes, such as trucks and trains. Due to their pivotal position, disruptions or operational inefficiencies at container terminals can have extensive downstream effects, propagating delays across supply chains and significantly increasing logistics costs (Dwitasari et al., 2021). Consequently, maintaining reliable and efficient container terminal operations is highly relevant, underscoring the necessity for reliability analysis and operational optimisation.

The developed model incorporates literature review and practical insights obtained through direct observations and expert discussions conducted during a two-day visit to Borusan Port, located in Bursa, Turkey. Interviews were conducted with seven employees across operational and management levels, who provided valuable explanations regarding terminal operations, common reliability issues, sources of operational delays, and current maintenance strategies. This engagement offered an understanding of real-world challenges faced by terminal operators, enabling the incorporation of realistic assumptions and accurate representations of container terminal reliability within the developed model. These insights ensure that the modelling approach reflects practical operational dependencies and failure mechanisms rather than purely theoretical assumptions, establishing a realistic foundation for the reliability analysis.

This chapter defines the operational and reliability context that forms the foundation for the modelling in the following chapters. The following sections outline the terminal's operational context and determined scope, maintenance activities, and provide an application of the Fault Tree Analysis (FTA) within the container terminal.

4.1. Container Terminal Operations

Understanding general operations is essential for system-level reliability analysis. Efficient handling of containers is critical to minimizing vessel turnaround times, reducing operational costs, and maintaining reliability in the supply chain (Voss, 2007). This section provides an overview of port operations, highlighting the flow of containers, key equipment used, and typical sources of operational complexity. The schematic of the container terminal system can be found in Figure 4.1, and the red box indicates the study scope.

The focus of this study is on modelling and analysing the reliability of key operational subsystems within a container terminal, particularly those most directly involved in the horizontal and vertical flow of containers during vessel emptying. The model scope includes quay crane (QC) operations, internal transport using horizontal-transport vehicles (HTs), and yard management with yard cranes (YCs). These three subsystems were selected because they represent the main transfer chain between vessel and yard, where most operational dependencies occur and delays are most likely to propagate through the terminal. Concentrating on the vessel emptying process allows for a consistent operational direction of container flow and avoids the added complexity of modelling both loading and discharging cycles simultaneously. Focusing on these subsystems enables the study to capture the dominant reliability

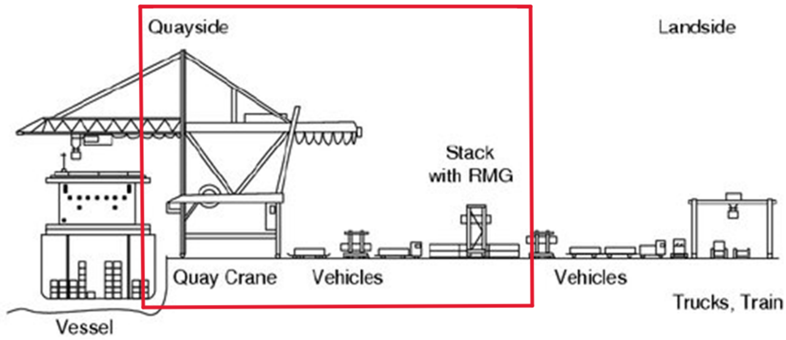


Figure 4.1: Container Terminal System (Adapted from Voss et al., 2004)

interactions that determine overall system performance while keeping the model tractable and focused on processes with the greatest operational impact.

Vessel arrival and berthing are not included in the model, as berth allocation has been widely studied. Gate and landside operations—including external truck scheduling and interactions with customs or rail—are also excluded from the reliability model. While operationally important, these elements are treated as boundary inputs that influence, but are not directly modelled within, the internal dynamics of quay-to-yard operations. The analysis therefore focuses on the terminal side of the process, capturing delays that originate within handling equipment, coordination, and internal transport rather than those caused by external scheduling or infrastructure constraints.

To understand the role of these subsystems within the wider terminal environment, the following sections describe the overall structure of terminal operations and how the selected elements interact with other processes.

4.1.1. Vessel Arrival and Berthing

The container terminal operations start with the arrival and berthing of vessels. Once a vessel is scheduled to arrive, it must be assigned to a suitable berth equipped with quay cranes, considering its dimensions, draft, and expected handling volume. This planning process, commonly referred to as the Berth Allocation Problem (BAP), aims to minimize vessel waiting and turnaround times, optimize the utilization of quay space, and support the smooth flow of subsequent operations. As noted by Voss et al. (2004), minimizing the time a ship remains at berth is a core objective, directly impacting operational performance and cost-efficiency.

Various studies have examined the berth allocation problem from different angles, all aiming to allocate berths in a way that reduces delays, prevents congestion, and enhances schedule reliability across the terminal. J. Luo et al. (2009) focuses on the Schedule Reliability Problem (SRP) for berth and crane allocation, aiming to reduce deviation between planned and actual vessel departure times.

4.1.2. Quay Crane Operations

Once a vessel is berthed, container handling operations begin with the deployment of cranes. These cranes transfer containers between the vessel and the quay. Ship-to-shore (STS) cranes, also referred to as Quay Cranes (QC), are typically rail-mounted gantries capable of moving both vertically and horizontally to access container bays onboard the ship. Their performance directly affects vessel turnaround time and overall terminal throughput. The operational cycle of an STS crane includes lifting a container from the vessel, transporting it across the quay, lowering it onto a waiting terminal tractor (TT) or an automated guided vehicle (AGV), and returning to the next pickup position. Weather conditions, particularly wind speed, can restrict crane operations due to safety concerns, while equipment failures and maintenance schedules introduce additional variability (Voss et al., 2004). Understanding these variability sources is important for the reliability model, as they represent the main operational and environmental factors affecting quay crane availability.

In addition to STS cranes, some container terminals, particularly smaller or mixed-use ports, also use Mobile Harbour Cranes (MHCs). These wheeled, free-standing cranes offer greater operational flexibility, as they can be repositioned between berths and adapted for various cargo types. However, they typically offer lower container handling speeds and throughput compared to STS cranes, making them more suitable for terminals with lower volumes or infrastructure constraints. In operation, STS performance is in the range of 22–30 boxes/h (Voss et al., 2004), while for the MHC 12-15 boxes/h can be expected. Equipment used for transferring the containers to land from the vessel can be found in Figure 4.2.

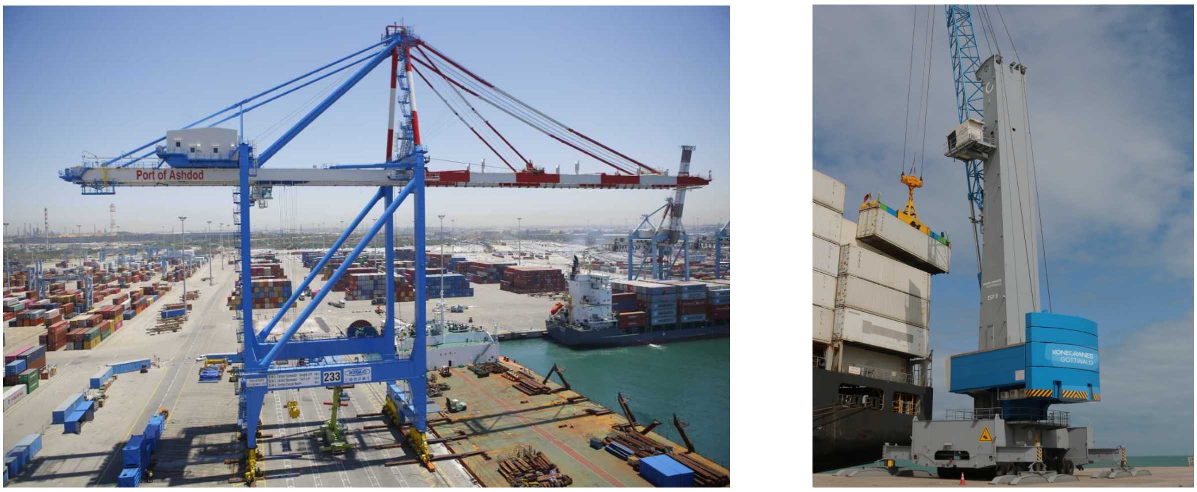


Figure 4.2: Left: Rail-mounted STS crane (Offshore Energy, 2021); right: Mobile Harbour Crane (MHC) (Container Management, 2020).

One of the critical challenges in crane operations is the coordination of multiple cranes on the same vessel. To prevent interference, adjacent cranes must maintain a safe buffer zone, limiting the number of cranes that can work simultaneously on a ship. Kizilay and Eliiyi (2021) highlights that optimizing crane assignment and sequencing is essential to reduce idle times and ensure balanced workloads.

4.1.3. Internal Transport

Internal transport refers to the horizontal movement of containers between the quay and the container yard. At many container terminals, this task is performed using Terminal Tractors (TTs), also known as yard trucks. Their flexibility and relatively low investment cost make them the most widely used transport method in terminals. Alternatively, Automated Guided Vehicles (AGVs) for internal container transport are used in automated terminals. AGVs are driverless, battery-powered units that follow pre-defined routes. While they offer benefits in terms of labour savings and 24/7 operation, AGVs require significant infrastructure investment and are best suited for terminals with high automation maturity. An image of an AGV can be found in Figure 4.3.

Figure 4.3: AGV used for internal transport (Konecranes, n.d.)

4.1.4. Yard Management

Yard management includes the stacking, retrieval, and reshuffling of containers, with the goal of maintaining efficient space utilization while minimizing re-handling. Containers in the yard are typically stored in blocks based on operational priorities such as export vs. import status, pickup times, destinations, or container type (e.g., refrigerated, hazardous) (Voss et al., 2004). The container yard functions as a buffer between quayside and landside operations, and effective yard planning is essential for preventing congestion, reducing dwell times, and supporting reliable vessel and truck turnaround. Improper stacking can lead to excessive reshuffling, which increases equipment usage, delays outbound operations, and reduces productivity.

To perform stacking and retrieval, container terminals typically use Rubber-Tyred Gantry (RTG) cranes or Rail-Mounted Gantry (RMG) cranes, also referred to as Yard Cranes (YC). RTGs offer high flexibility, as they are mobile and can navigate between different yard blocks. RMGs, by contrast, are fixed on rails and are often deployed in automated or semi-automated terminals with predictable flows and high-density storage layouts. An image of an RTG crane used in yard operations can be found in Figure 4.4.

Figure 4.4: RTG crane used in yard operations (Seven Industry, n.d.)

4.1.5. Gate and Landside Operations

Gate and landside operations form the critical interface between the container terminal and inland logistics systems. These operations manage the arrival and departure of external trucks and, where applicable, rail services that transport containers to and from inland destinations. The modal split of hinterland transportation is very specific for different terminals (Voss et al., 2004).

Upon arrival, external trucks typically enter through the terminal's in-gate, where container and vehicle data are checked and either filed into the terminal operating system or updated if a pre-advice was issued. After clearance, trucks proceed to designated transition points—locations where containers are loaded or unloaded by internal equipment, such as yard cranes or straddle carriers. These transition points may be located at the stack or within specific areas of the yard, depending on the terminal layout and handling system. Rail operations follow similar logistical requirements but often occur at a dedicated rail terminal within the yard. Trains are commonly loaded and unloaded by gantry cranes while the transports between the stack and the railhead are performed by straddle carriers, trucks or similar equipment (Voss et al., 2004).

4.2. Maintenance Strategies

Maintenance plays a critical role in ensuring the reliability of container terminal operations. Given the high interdependence of key equipment, even short periods of unplanned downtime can cause significant operational disruptions. QCs, in particular, are high-value assets whose failure directly affects vessel turnaround time. Similarly, HTs and YCs serve as vital links in the container flow between the quay and the yard; delays in their operation can quickly propagate and lead to system-wide inefficiencies. Maintenance policies strongly influence how often failures occur and how quickly operations recover, making them a key factor in overall terminal reliability.

4.2.1. Maintenance Types

Effective maintenance strategies are critical for ensuring the reliability of systems. Maintenance strategies range from traditional corrective and preventive methods to more advanced predictive approaches (Sang et al., 2021). Corrective maintenance (CM) is a reactive approach, addressing failures only after they occur, making it costly and unpredictable. Corrective maintenance can lead to high downtime and cost for critical components of the system.

In contrast, preventive maintenance (PM) involves scheduled interventions, reducing the risk of unexpected failures by performing maintenance at predefined intervals. However, fixed schedules do not account for actual equipment conditions, leading to either unnecessary maintenance or missed early fault detection. Preventive maintenance strategies are widely employed in medium- to large-sized terminals for cranes and yard systems, including the Borusan terminal.

Another maintenance strategy applicable for container terminals is predictive maintenance. This strategy relies on condition monitoring, sensors and data analytics. It can allow optimal timing, reduced risk and cost. However, it has high initial investment, so mostly applicable for highly automated terminals.

4.2.2. Preventive Maintenance Strategies by Equipment Type

Quay cranes (QCs) are the most critical and expensive assets in container terminal operations. Their availability has a direct impact on vessel turnaround time, and downtime can lead to a decrease in overall terminal throughput. At Borusan Port, QCs undergo time-based preventive maintenance, with regular checks and servicing carried out at fixed intervals, regardless of crane usage or load. There are different procedures they follow weekly, monthly, annually, biennially, and quadrennially. The weekly procedures involve visual inspections and functional checks of critical components to ensure proper operation and takes around three hours. As the maintenance intervals lengthen, the procedures become increasingly detailed. For instance, annual tasks include component lubrication, calibration, and the replacement of wear-prone parts. The most comprehensive maintenance is conducted every four years, during which the crane undergoes a complete checkup, including paint removal to check the welded components. This procedure spans over several days.

Rubber-Tyred Gantry (RTG) cranes are essential for yard operations, handling container stacking, retrieval, and reshuffling. While not as critical as quay cranes in determining vessel turnaround time, RTG availability directly affects yard efficiency and container dwell times. At Borusan Port, RTG maintenance follows a usage-based preventive strategy, with service intervals determined by operating hours rather than calendar time. The servicing frequency varies slightly depending on the crane's age. Older RTGs are maintained every 350 operating hours, while newer units follow a 450-hour interval, reflecting manufacturer guidance and operational experience. Although the original equipment manuals recommend 500-hour intervals, Borusan applies a more conservative threshold to enhance reliability and provide operational flexibility—allowing minor delays in maintenance scheduling without significantly increasing the risk of failure. Maintenance tasks at Borusan Port follow a structured hour-based system, where each milestone has a defined set of procedures. Every operating hour milestone has its own unique maintenance package, and some packages are performed repeatedly at later stages. Table 4.1 illustrates this cumulative structure for a newer RTG, with a check mark (✓) indicating which maintenance package is applied at each service point.

Table 4.1: RTG Maintenance Packages and Their Execution Schedule at Borusan Port

Package	**450**	**900**	**1350**	**1800**	**2250**	**2700**	**…**	**10,800**
450	✓	✓	✓	✓	✓	✓		✓
900		✓		✓		✓		✓
1350			✓			✓		✓
2700						✓		✓
10,800								✓

Automated Guided Vehicles (AGVs) and Terminal Tractors (TTs) play a central role in Horizontal Transport (HT) operations, facilitating container movement between the quay and the yard. At Borusan Port, TTs are maintained using a usage-based preventive maintenance strategy, similar to that applied to RTGs. Maintenance intervals are defined by the number of operating hours: 450, 900, 1350, 2700, and 10,800 hours, with procedures triggered at specific milestones. While the maintenance structure is similar, the operational strategy is more relaxed due to the built-in redundancy of the vehicle fleet. With multiple TTs and AGVs available at any given time, individual units can be cycled out for maintenance without significantly disrupting operations. This flexibility allows for easier alignment between servicing schedules and ongoing terminal activities, reducing the risk of bottlenecks while still maintaining high vehicle availability.

4.3. Fault Tree Analysis

To systematically identify and analyze potential failure possibilities within container terminal operations, an FTA model was developed. The FTA is a top-down, deductive reliability modelling method that begins with a defined system-level failure and explores the contributing events that could lead to it. In the case of a container terminal, the top event can be defined as the total system delay, representing a disruption to the terminal's ability to maintain efficient, uninterrupted operations.

In this study, QC Delay and HT Delay (Loaded) are treated as the primary contributors to the overall system delay. YC delay is incorporated as a contributing factor within the HT delay branch. This modelling choice reflects the operational logic of the terminal, where yard-side inefficiencies, such as slow yard crane performance or unavailability, primarily shows through delays in HTs waiting to unload.

The QC delay branch includes three main contributors: QC not being able to operate, low operational efficiency, and interface delays caused by unavailable HTs. A QC can be considered not working either due to mechanical failure or because it cannot operate under strong wind conditions. Wind, rain, and visibility limitations are modeled as the environmental causes that affect its efficiency. Additionally, even if the QC is operational, it may still experience idle time if it must wait for an empty HT to arrive.

The HT delay (loaded) branch reflects disruptions that occur while HTs are transporting containers from the quay to the yard. This delay can be caused by low HT availability or YC delay. The YC delay branch further includes two primary causes: YC failures and low YC efficiency. When storage is nearly full, yard operations slow down due to increased reshuffling and stacking constraints, leading to longer service times for inbound containers.

The FTA of the container terminal can be found in Figure 4.5.

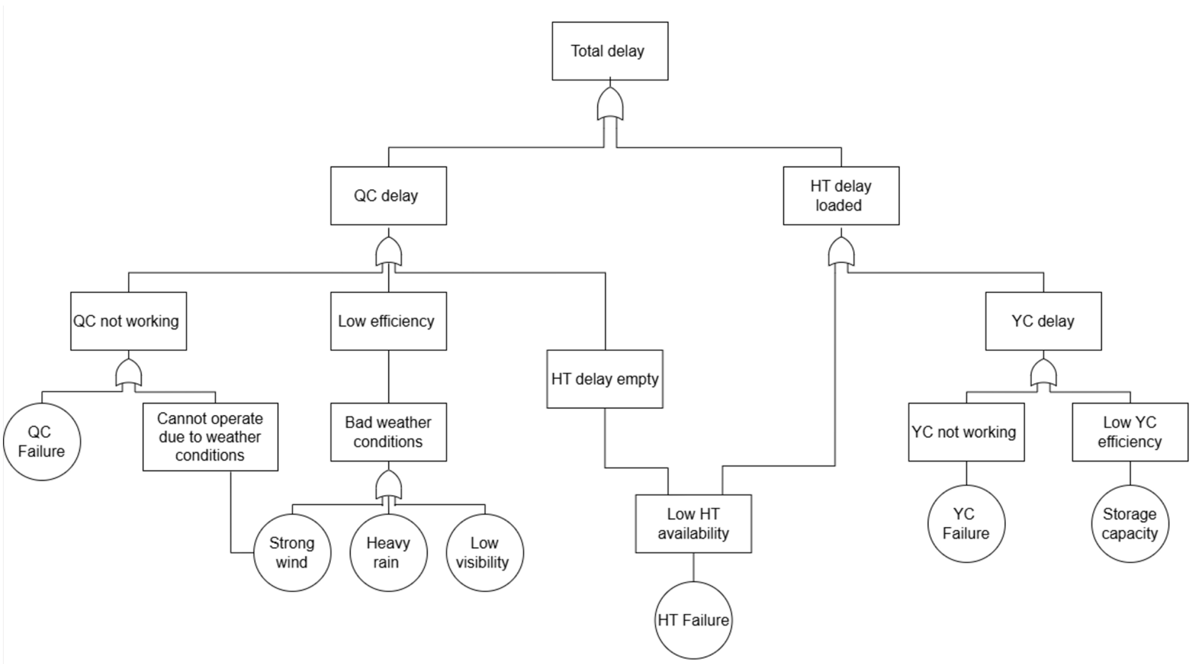


Figure 4.5: FTA of the container terminal

In summary, the fault tree defines the causal relationships among failures and operational conditions within the terminal system. These relationships are carried forward into the Bayesian Network (BN), which builds on the same structure to quantify how reliability losses and external factors contribute to delay propagation. This transition from fault-tree logic to probabilistic reasoning allows the study to quantify not only the likelihood of failures but also their cumulative effect on delay propagation under uncertainty. The next chapter presents this probabilistic model in detail.

5

Bayesian Network Construction

This chapter presents the development of the Bayesian Network (BN) used to analyse system reliability and delay propagation in the container terminal. The BN structure directly builds on the Fault Tree Analysis (FTA) described in Chapter 4, ensuring that each dependency in the network corresponds to a clearly defined operational relationship. The model is developed in two stages: a simplified 'base' BN and a more detailed 'complete' BN. The base BN represents the essential operational dependencies between subsystems and serves as a reference for sensitivity analysis. The full BN extends this structure by incorporating maintenance and operator availability nodes, providing a more realistic representation of terminal operations under varying conditions.

The following sections describe the BN components in increasing detail. Section 5.1 presents the overall BN structure and explains how the main subsystems are connected within the network. Section 5.2 introduces the node categories and their functional roles within the network. Section 5.3 outlines subsystem modeling for quay cranes (QCs), horizontal transport (HT), and yard cranes (YCs), including the formulation of Conditional Probability Tables (CPTs). Finally, the complete BN structure integrates maintenance and operator effects to support the performance analysis in Section 5.4.

5.1. Bayesian Network Structure

The top-level output node in the network is total delay, which aggregates delays caused by QCs, HTs, and YCs. This top event and the overall causal structure were derived directly from the FTA presented in Chapter 4. These three subsystems are modelled further through interdependent nodes capturing both direct failures and environmental or systemic inefficiencies. Both the base and complete models share this underlying structure, allowing a clear comparison between the simplified model and the detailed model.

The delay in the QC subsystem is driven by both operational status and efficiency. The QC availability node integrates multiple contributing factors: equipment condition, fleet availability, and weather-sensitive operability. In parallel, weather conditions also directly affect QC efficiency, representing reduced performance during poor visibility, strong winds, or precipitation. Additionally, the quay crane's performance is tightly coupled with the availability of HTs. Since container handoff from the QC to ground transport cannot occur without an empty HT, interruptions in HT return introduce waiting time for the QC.

The HT subsystem includes two main types of delay: HT delay empty and HT delay full. These capture scenarios where HTs are delayed while returning to the QC or while waiting to discharge full containers at the yard. Both are conditioned on the HT availability node, which integrates the operational readiness of the HT fleet based on vehicle health. In addition, terminal busyness affects HT Delay empty, as congestion and high operational load primarily slow down empty vehicles returning to the quay. Upstream, HT delay empty effects the QC delay, as the QC operations are impacted when empty HTs are unavailable. Downstream, HT delay full is influenced by YC delay, representing a bottleneck when yard cranes are unable to offload containers due to limited availability or reduced efficiency caused by storage capacity constraints. These interconnections between subsystems follow operational logic observed during the site visit and align with literature on container-terminal process coupling (Voss, 2007; Voss et al., 2004).

The complete BN structure extends the base structure by introducing nodes related to operators and by considering maintenance actions. Operator availability nodes for QC, YC, and HT subsystems capture potential disruptions due to labor shortages during day or night shifts or strikes. Maintenance effects are taking into account within the equipment health and availability, as maintenance actions improve the equipment health, while requiring downtime for the maintenance process to take place.

A simplified visualization of the complete BN structure can be found in Figure 5.1, providing an overall view of the structure. Nodes are color-coded according to their functional category—blue for environmental nodes, green for equipment health, yellow for availability, orange for efficiency, purple for operators, and red for delay nodes. Additionally, subsystems (QC, HT, YC) are highlighted to emphasize their internal structure and interactions.

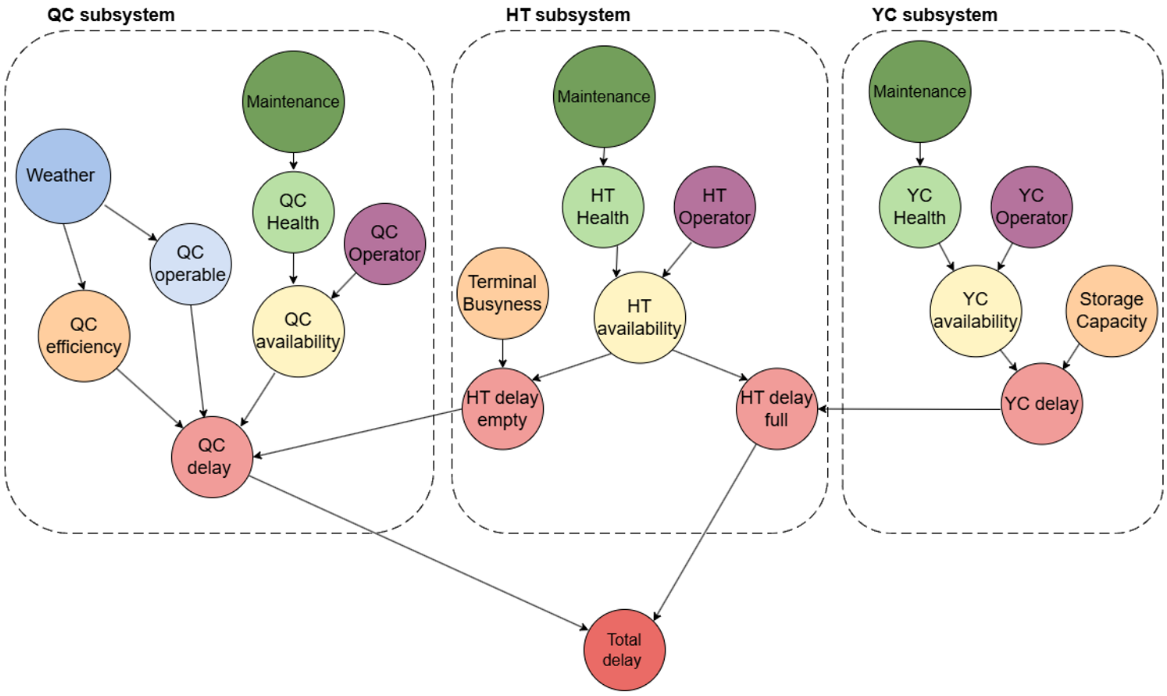


Figure 5.1: Simplified version of the complete BN structure

5.2. Node Categories

The BN is composed of a set of nodes grouped into different categories. These include nodes for equipment health, operator availability, environmental conditions, system availability and efficiency, and resulting delays. Each category captures a specific dimension of the system, enabling the model to represent both the immediate causes of disruption and the broader propagation of delays. The categories are illustrated in Figure 5.1, where nodes are color-coded by category and major subsystems are highlighted with bounding boxes. This section introduces each node type and outlines its general function within the overall network structure.

5.2.1. Equipment Health

Equipment health nodes represent the technical condition of QCs, HTs, and YCs. Each node captures the probability that the equipment remains operational based on the equipment's underlying mechanical state and age-dependent degradation. Failures are modelled using a Weibull distribution. The Weibull distribution is widely used in reliability engineering because of its flexibility to represent early-life, random, and wear-out failure patterns within a single formulation (Ebeling, 1996; Rausand and Høyland, 2004).

The Weibull distribution is flexible and can represent different failure behaviors through its shape parameter β and scale parameter η. A value $\beta < 1$ indicates a decreasing failure rate (early-life failures), $\beta = 1$ represents a constant failure rate, and $\beta > 1$ captures increasing failure likelihood due to aging or wear-out. The scale parameter η corresponds to the characteristic life, the time by which approximately 63% of components are expected to fail (Plousios, 2009).

Equipment age plays a central role for equipment health. New equipment exhibits low failure probability and long Mean Time Before failure (MTBF), while older equipment shows a higher likelihood of failure and shorter operational cycles. This can be reflected in the Weibull parameters: as equipment ages, the shape parameter β may increase slightly, capturing the accelerating failure rate, and the scale parameter η decreases, reflecting a shorter characteristic life. In this study, the equipment population is grouped into discrete age categories (new, mid-life, old), and each group is assigned corresponding β and η values reflecting these degradation effects, based on reported reliability data for comparable terminal equipment and adjusted proportionally across age groups.

The probability density function (PDF), $f(t)$, gives the instantaneous probability of failure at time t and is defined in Equation 5.1.

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-(t/\eta)^{\beta}}, \quad t \geq 0 \tag{5.1}$$

The cumulative distribution function(CDF), $F(t)$, gives the probability that the equipment has failed by time t. CDF can be calculated with Equation 5.2.

$$F(t) = \int_0^t f(\tau)\,d\tau = 1 - e^{-(t/\eta)^{\beta}} \tag{5.2}$$

The reliability function, $R(t)$, represents the probability that the equipment remains operational beyond time t. Reliability can be calculated with Equation 5.3 (Rosca et al., 2025).

$$R(t) = 1 - F(t) = e^{-(t/\eta)^{\beta}} \tag{5.3}$$

These three functions are closely connected: $f(t)$ is the instantaneous failure rate, $F(t)$ accumulates the probability of failure over time, and $R(t)$ gives the complementary probability of survival. The expected time to failure, also known as Mean Time Between Failures (MTBF), is computed from the reliability function as the mean of the survival time distribution. The equation used to find MTBF can be found in Equation 5.4 (Rosca et al., 2025).

$$\text{MTBF} = \int_0^{\infty} R(t)\,dt = \eta\,\Gamma\left(1 + \frac{1}{\beta}\right) \tag{5.4}$$

In the BN, preventive and corrective maintenance are incorporated conceptually through their influence on equipment health. In the base model, only corrective maintenance is considered, and a perfect maintenance assumption is applied. This implicates that after each failure, the equipment is fully restored to an as-good-as-new condition, restarting the reliability cycle. Preventive effects, which partially restore equipment condition through scheduled interventions, are introduced later in the complete model. The detailed formulation and parameterization of these effects are presented in the maintenance modeling section (Section 5.4.1).

5.2.2. Availability

In this model, availability represents the expected proportion of operational equipment within each subsystem (QC, HT, or YC) rather than the state of a single machine. Building on the reliability characteristics derived from the Weibull model, this proportion reflects how frequently the subsystem can operate relative to its total potential uptime. In the BN, the expected availability of each piece of equipment is calculated by combining the MTBF with the Mean Time to Repair (MTTR), with the Equation 5.5 (Lv et al., 2010).

$$A = \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}} \tag{5.5}$$

MTTR is modelled as a truncated Normal distribution to capture variability in corrective maintenance durations, given in Equation 5.6 (Szpytko & Salgado Duarte, 2021). This represents the spread of typical repair times around an average value while avoiding non-physical negative durations.

$$\text{MTTR} \sim \text{TruncatedNormal}(\mu_{\text{MTTR}}, \sigma_{\text{MTTR}}, 0, \infty) \tag{5.6}$$

The continuous availability A is then discretized into three operational states—Low, Medium, and High. For QCs and YCs, the thresholds are set at $[0.0,\ 0.92,\ 0.97,\ 1.0]$, where values below 0.92 correspond to a Low state, between 0.92 and 0.97 to Medium, and above 0.97 to High availability. For horizontal transport (HT), higher nominal availability is assumed due to fleet redundancy, with thresholds $[0.0,\ 0.95,\ 0.98,\ 1.0]$. These thresholds are assumed values, selected to capture the full range of operational conditions from reduced readiness to near-continuous availability across all subsystems.

Smoothed thresholds were used to avoid abrupt transitions between categories and reduce artificial sensitivity to small parameter changes. The probabilities for these states are defined in Equation 5.7, where a small smoothing margin δ controls the gradual transition between categories, and A_{low} and A_{high} specify the thresholds separating Low, Medium, and High availability levels. A margin of $\delta = 0.05$ is used in this study as a modeling assumption, chosen to provide a smooth yet responsive transition between states. This formulation ensures that small variations in MTBF or MTTR do not cause unrealistic jumps between discrete availability states.

$$\begin{aligned}
p_{\text{Low}} &= \max\left(0, \min\left(1, \frac{A_{\text{low}} + \delta - A}{2\delta}\right)\right) \\
p_{\text{High}} &= \max\left(0, \min\left(1, \frac{A - A_{\text{high}} + \delta}{2\delta}\right)\right) \\
p_{\text{Med}} &= 1 - p_{\text{Low}} - p_{\text{High}}
\end{aligned} \tag{5.7}$$

In the complete BN, preventive maintenance interventions are also incorporated. While maintenance improves the effective reliability of equipment by reducing its virtual age, it temporarily reduces availability due to scheduled downtime. For the complete model, this preventive downtime is included in the availability calculation, enabling the network to capture both the benefits and the short-term interruptions of maintenance activities. The detailed formulation of this effect is presented in Section 5.4.1.

During maintenance analysis, slightly lower availability thresholds are applied to reflect the imperfect nature of corrective maintenance (Pham & Wang, 1996; H. Wang, 2002). For all subsystems, the thresholds are set to $[0.0,\ 0.88,\ 0.95,\ 1.0]$, corresponding to Low, Medium, and High states. These adjusted values capture the progressive degradation of equipment condition and provide a more realistic representation of long-term operational performance compared to the idealized base model (Gothandapani et al., 2024).

5.2.3. Environmental Conditions

Weather nodes represent external factors that influence the terminal's operating conditions such as wind speed, visibility, and precipitation. These variables are modelled with categorical probability distributions with discrete levels (e.g., low, moderate, high) derived from historical data. In this study, long-term daily records from the Royal Netherlands Meteorological Institute (KNMI) are used as an illustrative example to define the state probabilities; these can be updated or replaced if more detailed, location-specific data become available.

Weather conditions influence both the operability and efficiency of QCs. Under strong wind conditions, operations are suspended for safety, while moderate wind, rain, or reduced visibility slow down lifting and positioning, lowering overall handling efficiency. Unlike health or operator nodes, environmental nodes are exogenous inputs to the network, introducing stochastic variability and representing real-world constraints beyond the control of terminal operations. In this model, the weather influence is limited to quay cranes, as their performance is most directly affected by external conditions, while the impact on other equipment types is disregarded for simplicity. Further information on the weather conditions and how they effect the operations can be found in Appendix B.

5.2.4. Efficiency

Efficiency nodes quantify the effective operational performance of each subsystem under prevailing constraints, representing how quickly and effectively equipment can perform its tasks when available. Unlike availability, which captures whether a piece of equipment can operate at all, efficiency measures how well it performs under given conditions.

For QCs, efficiency is primarily determined by weather conditions—including wind, rain, and visibility—which can reduce lifting speed, accuracy, or force temporary operational slowdowns. For HT, efficiency reflects terminal busyness and congestion, capturing delays caused by limited vehicle availability, waiting times, or queueing at handover points. For YC, efficiency is affected by storage area utilization, as high yard occupancy increases reshuffling operations and slows container stacking and retrieval.

5.2.5. Operator Availability

The operator availability node is only relevant for the complete BN model. It introduces a human-performance factor into the BN, allowing the model to reflect workforce-related uncertainties in terminal operations. Operator availability nodes represent the presence of qualified personnel required to operate QC, HT, and YC. These nodes are modelled using three discrete states: fully available, partially available, and unavailable. This structure captures the variability in staffing levels across different operational shifts—such as day, evening, and night—as well as the potential for labor disruptions, including strikes or unexpected absences.

5.2.6. Delay Nodes

Delay nodes capture the primary output variables of the BN, linking subsystem reliability to overall terminal performance at both the subsystem level—such as QC, HT, and YC delay—and the overall terminal level via the Total Delay node. These nodes are influenced by a combination of factors, including equipment availability, operational efficiency, and interdependencies between subsystems.

Each delay node is modelled using discretized states (e.g., low delay, moderate delay, severe delay), allowing the network to support probabilistic reasoning under uncertainty. A low delay state represents normal operation or only minor inefficiencies that have little or no observable effect on overall system performance. A moderate delay reflects noticeable but manageable disruptions, such as temporary slowdowns or localized congestion within a subsystem. A severe delay corresponds to major disruptions where system performance is significantly reduced. This structure enables the model to simulate varying operational scenarios, assess the impact of disruptions, and infer the most likely causes of observed delays.

5.3. Subsystem Modeling

To operationalize the node categories and conditional dependencies described earlier, the BN is structured around three core subsystems that reflect the physical and functional architecture of the terminal: QC, HT, and YC operations. In this section, the focus is on the base BN, which models terminal operations using equipment health, operability, efficiency, and environmental factors, without including preventive maintenance actions or operator availability. Each subsystem integrates equipment health, operability, efficiency, and interaction logic into delay outcomes. This section outlines how the various node types are used within each subsystem, and how interdependencies between them propagate effects across the terminal.

5.3.1. Quay Crane Subsystem

The QC subsystem is modelled to capture both the functional status and performance variability of the QC subsystem under changing environmental and operational conditions. This part of the network includes nodes that represent the equipment health, operability, efficiency, and coordination with the internal transport system.

Environmental Effect The QC efficiency and QC operability are directly influenced by environmental conditions. As described in Section 5.2.3, these are represented in the BN by three weather-related nodes: Wind, Rain, and Visibility. These factors quantify operational constraints due to high winds, precipitation, and reduced visibility, which can reduce lifting speed, accuracy, or necessitate temporary shutdowns. In the BN, each weather variable is discretized into a small number of states representing increasing severity (e.g., Beaufort wind levels, rain intensity, fog density), and their probabilities are derived from historical measurements at KNMI station 344 in Rotterdam as an example dataset. The combined influence of these nodes is incorporated into the 'QC Efficiency' node, modifying the QC's operational throughput under adverse conditions. For full details on the node definitions, categories, probability distributions, and estimated efficiency impacts, see Appendix B.

QC operability The QC operability node models whether the QC can function under the given environmental conditions, specifically wind. It is conditionally dependent on the 'Wind' node, which is explained further in section B.1. The wind node categorizes wind strength into three levels aligned with the Beaufort scale: normal conditions, strong wind (Beaufort 6–7), storm (Beaufort 8 or higher) (National Weather Service, 2023). Operational policies at container terminals typically restrict crane usage under extreme wind conditions due to safety risks (van den Bos, 2015). Reflecting this, the model assumes that cranes remain fully operable under normal and moderate wind conditions, but become inoperable when wind levels reach Beaufort 8 or above.

QC Efficiency The performance of the QC is further refined through the 'Efficiency' node, which quantifies the QC's effective operational throughput under current environmental conditions. This node is conditionally dependent on weather nodes 'Wind', 'Rain', and 'Visibility', detailed in Appendix B. Efficiency is evaluated only when the QC is operable; otherwise, it is assigned the lowest efficiency level to represent a non-functional state.

Environmental effects are modelled using multiplicative modifiers derived from expert judgement provided by a QC operator during the Borusan Port visit. Environmental multiplicative factors used for QC efficiency can be found in Table 5.1.

Table 5.1: Environmental multiplicative factors for QC efficiency

Environmental Factor	State	Multiplier
Wind	Low	1.0
	Medium	0.7
	High	0.0
Rain	None	1.0
	Light	0.95
	Moderate	0.85
	Heavy	0.7
Visibility	Clear	1.0
	Light Fog	0.95
	Moderate Fog	0.85
	Dense Fog	0.7

The efficiency value can be calculated using Equation 5.8. The resulting scalar efficiency score, ranging from 0 to 1, is then discretized into 10 bins representing operational efficiency levels from 0–10% up to 90–100%, where bin 1 corresponds to the highest efficiency, and bin 10 to the lowest.

$$\text{Efficiency} = \text{Wind Multiplier} \times \text{Rain Multiplier} \times \text{Visibility Multiplier} \tag{5.8}$$

QC health and availability QC health is modelled using a Weibull distribution, capturing the age-dependent probability of failure. The shape parameter β is set to 1.2 for new cranes, 1.5 for mid-aged cranes, and 2.0 for old cranes, reflecting progressive wear-out behavior (Ebeling, 1996). The scale parameter η is assigned values of 600, 500, and 400 hours, respectively. These values were adapted from the mean time to failure of approximately 1200 hours reported for similar QCs (Szpytko & Salgado Duarte, 2021) and adjusted downward to represent a conservative scenario without any preventive maintenance, in which older equipment is expected to fail more frequently. In the BN, these parameters are used to compute the mean time between failures (MTBF) for each age category.

The mean time to repair (MTTR) is modelled with a truncated normal distribution, using a mean of 24 hours and a standard deviation of 12 hours, consistent with observed repair durations in crane operations (Szpytko & Salgado Duarte, 2021). In the BN, the resulting Weibull parameters and MTTR distribution are used to compute subsystem availability and the conditional failure probabilities for each crane age category.

QC delay The QC Delay node captures the total delay experienced by a QC, combining effects from its operational state, availability, environmental efficiency, and interaction with HT.

The QC operability acts as a hard gate: when wind conditions exceed operational thresholds, QCs are assumed to be inoperable, and the node is set deterministically to a high delay state. When QCs are operable, the probability of delay is then influenced by the three other factors. Lower availability increases the likelihood of malfunctions or reduced performance; poor environmental efficiency (driven by wind, rain, and visibility) reduces handling speed; and high HT (Empty) delays prevent the continuous supply of horizontal transport vehicles, creating idle time at the quay side operations. CPD table used for the QC Delay node can be found in Table 5.2. These probabilities were defined based on expected cause–and–effect relationships between subsystem conditions and delay outcomes.

Table 5.2: Conditional probabilities for QC delay, when the QC is operable

QC Availability	HT Delay (Empty)	Eff 1–3			Eff 4–7			Eff 8–10		
		Low	Med	High	Low	Med	High	Low	Med	High
High	High	0.60	0.20	0.20	0.45	0.30	0.25	0.35	0.40	0.25
	Med	0.70	0.20	0.10	0.70	0.25	0.05	0.50	0.35	0.15
	Low	0.90	0.10	0.00	0.80	0.20	0.00	0.70	0.30	0.00
Medium	High	0.00	0.30	0.70	0.00	0.28	0.72	0.00	0.25	0.75
	Med	0.10	0.25	0.65	0.05	0.28	0.67	0.05	0.25	0.70
	Low	0.20	0.20	0.60	0.18	0.20	0.62	0.10	0.25	0.65
Low	High	0.00	0.10	0.90	0.00	0.08	0.92	0.00	0.05	0.95
	Med	0.00	0.15	0.85	0.00	0.13	0.87	0.00	0.10	0.90
	Low	0.00	0.20	0.80	0.00	0.18	0.82	0.00	0.15	0.85

5.3.2. Horizontal Transport Subsystem

The HT subsystem models the internal transport component of the container terminal, specifically focusing on the movement of containers between the quay and yard areas. It captures both the operational availability of the HT fleet and the delays that arise from bottlenecks at handover points with other subsystems.

HT health and availability HT health is modelled using a Weibull distribution. All HT types, including Automated Guided Vehicles (AGVs) and terminal tractors (TTs), are assumed to share the same parameters due to the lack of specific reliability data. The parameters were chosen to represent the reliability between QCs and YCs, reflecting an average expected operational performance. The scale parameter η was set to 400 for new vehicles, 350 for mid-aged vehicles, and 300 for old vehicles. The shape parameter β is assumed to be the same as for QCs: 1.2 for new, 1.5 for mid-aged, and 2.0 for old vehicles. The MTTR is assumed to be 8 hours with a standard deviation of 4 hours, consistent with the parameters used for QCs and YCs, reflecting shorter repair times than QC and YC.

Terminal busyness The node ‘Terminal Busyness’ captures the overall operational load in the terminal at a given time, reflecting how crowded or active the quay and yard areas are. It is modelled as a categorical variable with three discrete states-Low, Normal, and High—corresponding to assumed probabilities of 0.2, 0.6, and 0.2, respectively. This distribution reflects typical operational conditions, where normal busyness is most frequent, while low or high activity occurs less frequently. Terminal Busyness influences 'HT Delay Empty', affecting the likelihood of delays due to congestion or coordination challenges within the terminal.

HT Delay Empty HT delay is modelled using two separate nodes to reflect operational context: 'HT Delay Empty' captures delays when HTs are returning empty from the yard to the quay, while 'HT Delay Loaded' models delays while transporting full containers from the quay to the yard. This separation allows the model to capture both the QC-HT and HT-YC interactions more accurately.

The node 'HT Delay Empty' is conditionally dependent on two parent nodes: 'HT Availability' and 'Terminal Busyness'. As HT availability decreases or busyness increases, the likelihood of moderate or high delay rises due to reduced vehicle redundancy and increased operational demand. The CPD was defined with three states for both parent nodes—High, Medium, and Low—reflecting the combined effect of equipment readiness and terminal congestion. The values used for the CPD are based on assumptions derived from cause–and–effect relationships between availability, busyness, and delay, and can be found in Table 5.3.

Table 5.3: Conditional probabilities for 'HT Delay Empty' based on HT Availability and Terminal Busyness

Parent Nodes		**HT Delay Empty**		
HT Availability	**Terminal Busyness**	**Low**	**Moderate**	**High**
High	Low	0.8	0.15	0.05
High	Medium	0.7	0.20	0.10
High	High	0.6	0.30	0.10
Medium	Low	0.6	0.30	0.10
Medium	Medium	0.5	0.30	0.20
Medium	High	0.3	0.40	0.30
Low	Low	0.3	0.30	0.40
Low	Medium	0.2	0.30	0.50
Low	High	0.1	0.30	0.60

HT Delay Loaded The node 'HT Delay Loaded' captures delays encountered by HT while moving full containers from the quay to the yard. It is conditionally dependent on two parent nodes: 'HT Availability' and 'YC Delay'. This structure represents the operational dependency between the readiness of the HT fleet and the capacity of yard-side operations: low HT availability or high YC delay increases the likelihood of moderate or severe delay.

The CPT accounts for all combinations of three HT availability levels (High, Medium, Low) and three YC delay states (Low, Medium, High), resulting in a 3×3 input configuration. When availability is high and YC delays are low, the probability of delay is minimal. Conversely, low availability combined with high YC delays produces the highest of the severe delays. The conditional probabilities assumed in the model are summarized in Table 5.4.

5.3.3. Yard Crane Subsystem

The YC subsystem models the performance of the container stacking and retrieval process within the terminal's yard area. This subsystem is essential for completing the vessel emptying cycle and directly influences the overall efficiency of HT operations and container placement logistics.

YC health and Availability YC health is modeled using a Weibull distribution to represent the age-dependent probability of failure. The scale parameter η is set to 300 for new, 250 for mid-aged, and 220 for old yard cranes, while the shape parameter β is set to 1.2, 1.5, and 2.0, respectively. Reported reliability values for YCs are typically provided as mean moves between failures (MMBF); these were converted to MTBF by assuming an average handling rate of 25 moves per hour (*Automatic Stacking*

Table 5.4: Conditional probabilities for ‘HT Delay Loaded’ based on HT Availability and YC Delay

Parent Nodes		HT Delay Loaded		
HT Availability	**YC Delay**	**Low**	**Moderate**	**High**
High	Low	0.9	0.1	0.0
High	Medium	0.8	0.2	0.0
High	High	0.7	0.2	0.1
Medium	Low	0.6	0.3	0.1
Medium	Medium	0.5	0.3	0.2
Medium	High	0.4	0.4	0.2
Low	Low	0.3	0.3	0.4
Low	Medium	0.2	0.3	0.5
Low	High	0.0	0.2	0.8

Crane Performance, 2018). The resulting MTBF values were then compared with those of QCs to derive consistent scale parameters.

MTTR is modeled using a truncated normal distribution with a mean of 14 hours and a standard deviation of 7 hours, representing moderately complex repair activities—less demanding than for QCs but more time-consuming than for HTs. These parameters are consistent with the reliability assumptions applied across the other subsystems and are used to compute the expected availability of the YC subsystem in the BN.

Storage Capacity Level The node ‘Storage Capacity Level’ represents the overall yard utilization (fullness), categorizing yard utilization into three discrete states: Low (<30%), Medium (30–70%), and High (>70%). Based on typical operational conditions, these states are assigned probabilities of 0.2, 0.4, and 0.4, respectively. This node serves as a parent to ‘YC Delay’, influencing how efficiently YCs can perform stacking and retrieval operations under varying yard congestion.

Yard Crane Delay The node ‘YC Delay’ represents delays occurring during container handling in the yard and is conditionally dependent on two parent nodes: ‘YC Availability’ and ‘Storage Capacity Level’. This structure captures how both the technical readiness of YCs and the level of yard utilization jointly affect operational performance. Low availability or high storage occupancy increases the likelihood of moderate or high delays due to reduced equipment capacity and more complex container handling.

The CPT accounts for all combinations of three yard crane availability levels (High, Medium, Low) and three storage capacity states (Low, Medium, High), resulting in a 3×3 input configuration. When availability is high and storage utilization is low, delays are minimal. Conversely, low availability combined with high storage occupancy produces the highest risk of severe delays. The conditional probabilities assumed in the model are summarized in Table 5.5.

Table 5.5: Conditional probabilities for ‘YC Delay’ based on YC Availability and Storage Capacity Level

Parent Nodes		YC Delay		
YC Availability	**Storage Capacity Level**	**Low**	**Moderate**	**High**
High	Low	0.8	0.15	0.05
High	Medium	0.7	0.2	0.1
High	High	0.6	0.25	0.15
Medium	Low	0.5	0.3	0.2
Medium	Medium	0.4	0.4	0.2
Medium	High	0.3	0.4	0.3
Low	Low	0.2	0.3	0.5
Low	Medium	0.1	0.3	0.6
Low	High	0.0	0.2	0.8

5.3.4. Total Delay

The node 'Total Delay' represents the overall operational delay of the sea-side of the terminal, combining upstream delays from both quay-side and yard-side operations. It is conditionally dependent on two parent nodes: 'QC Delay', which captures QC–related delays, and 'HT Delay Loaded', which represents disruptions in internal transport while moving full containers from the quay to the yard. This structure reflects the two critical operational segments that most directly influence terminal turnaround time. Delays in either segment—whether due to reduced QC efficiency, waiting for HT, or yard-side congestion—can propagate and accumulate, amplifying the total delay. High delays in one or both subsystems dominate the outcome, while low delays in both result in minimal total delay.

The CPT accounts for all combinations of three delay states in each parent node (Low, Medium, High), resulting in a 3×3 configuration. When both QC and HT Delay Loaded are low, the total delay is minimal. If one subsystem experiences high delay, it substantially increases the probability of moderate or high total delay. When both parent nodes are in the high-delay state, total delay is almost certain to be high. The conditional probabilities assumed in the model are summarized in Table 5.6.

Table 5.6: Conditional probabilities for 'Total Delay' based on Crane Delay and HT Delay Loaded

Parent Nodes		Total Delay		
QC Delay	**HT Delay Loaded**	**Low**	**Moderate**	**High**
Low	Low	0.90	0.10	0.00
Low	Medium	0.55	0.35	0.10
Low	High	0.35	0.45	0.20
Medium	Low	0.10	0.40	0.50
Medium	Medium	0.10	0.35	0.55
Medium	High	0.05	0.30	0.65
High	Low	0.00	0.10	0.90
High	Medium	0.00	0.05	0.95
High	High	0.00	0.00	1.00

5.4. Complete BN Model

The complete BN model extends the base reliability structure by explicitly integrating preventive maintenance and operator-related factors, representing the two main controllable dimensions of terminal performance. This section explains how preventive maintenance and operator availability influence the system reliability and availability.

5.4.1. Maintenance Modelling

Maintenance activities were included in the reliability framework to show how preventive maintenance (PM) and corrective maintenance (CM) affect system performance over time.

Preventive maintenance is planned and carried out while the system is still working. Its main goal is to slow down degradation, restore some functionality, and prevent sudden failures. Each PM event temporarily boosts the system's reliability by extending its effective lifetime and slightly slowing the wear-out rate. To represent these effects quantitatively, PM in the model adjusts the Weibull parameters of the equipment's lifetime distribution. With PM activities, the scale parameter representing the characteristic life increases, while the shape parameter decreases just enough to show a slower deterioration rate. The extent of improvement depends on the level of maintenance—minor, medium, or major—each having a specific duration and effectiveness factor.

In contrast, corrective maintenance is done after a failure happens. Its purpose is to restore operability, and the system typically resumes service in a condition short of its original performance. The expected downtime from corrective actions is shown through the mean time to repair (MTTR), which reflects the average length of unplanned outages.

Imperfect Maintenance and Virtual Age Modelling In practice, neither type of maintenance fully restores the system to an "as-good-as-new" condition. Maintenance activities are usually imperfect

(Jacopino et al., 2004, 2006; Pham and Wang, 1996; Pingjian Yu et al., 2008; Tanwar et al., 2014; H. Wang, 2002). They improve reliability to some extent, but leave some wear and degradation (Pham and Wang, 1996; H. Wang, 2002). To explain this behavior, the imperfect maintenance model used in this study follows the theoretical framework created by Kijima (1989). This framework generalizes maintenance actions using the idea of virtual age.

Traditional reliability analysis makes a distinction between two idealized repair processes: the Ordinary Renewal Process (ORP), which represents perfect repair that brings the system back to a new condition, and the Non-Homogeneous Poisson Process (NHPP), which represents minimal repair that leaves the system “as-bad-as-old” (X. Liu et al., 2020). Kijima’s Generalized Renewal Process (GRP) adds a restoration factor $\rho \in [0, 1]$ to describe the range between these two extremes (Ferreira et al., 2015; Kijima, 1989; Pham and Wang, 1996; H. Wang, 2002; Yevkin and Krivtsov, 2012). When $\rho = 0$, the system is completely renewed (perfect repair). When $\rho = 1$, it undergoes minimal repair (no rejuvenation). When $0 < \rho < 1$, maintenance is imperfect, resulting in a condition that is better than old but worse than new.

This concept is formalized through Kijima’s virtual-age models, which show how the effective age of a system changes after maintenance. In the Type I formulation, the system’s virtual age after the n-th maintenance event can be represented with Equation 5.9.

$$V_n = V_{n-1} + \rho_n X_n, \tag{5.9}$$

Here, X_n represents the operating time since the last intervention, and ρ_n is the restoration factor. This formulation realistically shows the partial rejuvenation effect of maintenance. Each intervention reduces some of the accumulated wear without completely resetting the system’s condition.

In this study, the Type I model is applied to preventive maintenance, which gradually restores the equipment and extends its lifetime. Type I was chosen because it represents partial rejuvenation as an additive function of operating time, making it suitable for PM events applied at regular intervals (Kijima, 1989; Pham & Wang, 1996). Type II, by contrast, models proportional rejuvenation of the total virtual age, which is more appropriate for cumulative overhauls rather than routine PM (H. Wang, 2002). Corrective maintenance is represented by the NHPP minimal-repair case, which returns functionality but does not improve the underlying condition (X. Liu et al., 2020). This formulation adds a layer of complexity compared to the base model, which assumes perfect restoration, but it provides a more realistic representation of equipment behaviour over repeated maintenance cycles.

Preventive maintenance types and frequencies Three levels of PM are considered, representing increasing scope, level of detail, and duration; namely, minor, medium, and major. Minor PM activities are brief and limited in scope, typically carried out at short time intervals. Medium PM involves more detailed procedures then minor, but not as detailed as major. Major PM represents comprehensive interventions that require significant time and planning, are assumed to take the longest downtime. To evaluate the effect of maintenance scheduling on equipment reliability, these three PM types are tested under weekly, monthly, and yearly frequencies, representing alternative maintenance policy scenarios within the model.

In the BN model, each preventive maintenance type (*Minor*, *Medium*, *Major*) is represented as a probabilistic node with four possible policy states: *None*, *Weekly*, *Monthly*, and *Yearly*. These categorical states determine the expected number of interventions per year (n_t), which in turn influences the annual maintenance effectiveness (E_η, E_β). This structure allows the model to sample or evaluate different maintenance portfolios and quantify their impact on availability and reliability under uncertainty.

Maintenance effect by type Each PM type applies a pair of improvement multipliers, e_η and e_β, to the Weibull scale and shape parameters, respectively. The assumed factors can be found in Table 5.7, reflecting the relative impact of each intervention type.

Table 5.7: PM multipliers applied to Weibull parameters

PM Level	η (Scale Factor)	β (Shape Factor)
Minor	0.10	0.05
Medium	0.25	0.15
Major	0.60	0.30

The scale multiplier e_η represents the fractional increase in effective lifetime (MTBF) achieved by each PM event, while the shape multiplier e_β adjusts the degradation rate. The assumed factors aim to capture that more intensive PM (e.g., major overhauls) yields larger improvements in the equipment's virtual age.

Maintenance effectiveness In practice, a system's overall reliability improvement results from the combined effect of several PM types performed at different intervals. To capture this interaction, the cumulative annual maintenance effectiveness is computed using the formulation shown in Equation 5.10, which follows the same principle used to combine independent reliabilities in parallel systems (Rausand and Høyland, 2004). This ensures that the marginal benefit of each additional maintenance activity decreases as total frequency increases.

$$E_\eta = 1 - \prod_{t\in\{\text{Minor, Medium, Major}\}} (1 - e_{\eta,t})^{n_t/F_N}, \tag{5.10}$$

In this expression, each maintenance type t contributes independently to the overall improvement. $e_{\eta,t}$ denotes the per-event effectiveness of type t, and n_t the number of events per year. Frequency normalization factor F_N is used to preventing the model from overestimating rejuvenation when maintenance is done very frequently and is set to 12. The resulting E_η approaches unity asymptotically, preventing unrealistically large cumulative gains. Although the cumulative effectiveness E_η is not used directly to update the adjusted scale parameter η', it provides a useful measure of the overall preventive-maintenance performance.

A similar formulation is used for E_β, and can be found in Equation 5.11.

$$E_\beta = 1 - \prod_{t\in\{\text{Minor, Medium, Major}\}} (1 - e_{\beta,t})^{n_t/F_N}, \tag{5.11}$$

Adjustment of Weibull parameters The baseline Weibull parameters (η_0, β_0) represent the characteristic life and wear-out rate of the equipment in the absence of maintenance. To reflect the partial rejuvenation achieved through PM, these parameters are updated to (η', β'). The adjustment accounts for the cumulative influence of all PM activities—minor, medium, and major—performed during the year, incorporating both their frequency and effectiveness.

The scale parameter η' determines the characteristic life of the equipment and is modified according to the retained-age fraction ϕ, which expresses the proportion of degradation that remains after maintenance, and is given in Equation 5.12.

$$\eta' = \frac{\eta_0}{\phi}. \tag{5.12}$$

In this expression, a smaller ϕ corresponds to a stronger rejuvenation effect, leading to a longer effective lifetime ($\eta' > \eta_0$). The retained-age fraction ϕ is computed from the restoration factors ρ_t associated with each maintenance level, as shown in Equation 5.13.

$$\phi = (1 - \rho_{\text{min}})^{n_{\text{min}}/F_N} (1 - \rho_{\text{med}})^{n_{\text{med}}/F_N} (1 - \rho_{\text{maj}})^{n_{\text{maj}}/F_N}. \tag{5.13}$$

Here, ρ denotes the per-event rejuvenation fraction—the proportion of accumulated wear that is removed by a maintenance activity of type t. Higher values of ρ therefore correspond to stronger rejuvenation and greater lifetime extension. In this study, the rejuvenation fractions were set to $\rho_{min} = 0.10$,

$\rho_{med} = 0.30$, and $\rho_{maj} = 0.60$, representing progressively more effective interventions for higher maintenance levels.

The shape parameter β' defines the rate at which the failure probability increases with time. Maintenance actions can slightly reduce this rate by smoothing the wear-out process, leading to a lower β' value than the baseline. The adjusted β' is given in Equation 5.14.

$$\beta' = \beta_0 \left[1 - \min\left(B_\beta E_\beta, \text{Max beta drop}\right)\right]. \tag{5.14}$$

where E_β represents the overall annual effectiveness of PM in moderating the wear-out rate, B_β is a sensitivity coefficient controlling how strongly maintenance affects β. In this study, B_β is set to 0.5, representing a moderate influence of maintenance on the shape parameter. Maximum beta drop is set to 0.30 to limit the maximum reduction in β to prevent unrealistic flattening of the failure distribution. A lower β' indicates that failures become less concentrated toward the end of life, representing a smoother deterioration trend after effective maintenance.

Preventive maintenance downtime PM durations differ between equipment types and levels of intervention. Table 5.8 summarizes the assumed average duration of each PM event, expressed in hours.

Table 5.8: Average duration of preventive maintenance events (hours per intervention).

Equipment Type	Minor PM	Medium PM	Major PM
Quay Crane	2	6	24
Yard Crane	3	6	20
Horizontal Transport	1	2	4

The total annual preventive-maintenance downtime can be computed with Equation 5.15, where n denotes the number of PM events per year and t denotes their respective durations from Table 5.8, depending on the type of equipment.

$$T_{\text{PM,year}} = n_{\text{Minor}} \cdot t_{\text{Minor}} + n_{\text{Medium}} \cdot t_{\text{Medium}} + n_{\text{Major}} \cdot t_{\text{Major}} \tag{5.15}$$

Availability under minimal repair Operational availability is computed using the minimal-repair (NHPP) formulation rather than the perfect-repair approximation (X. Liu et al., 2020). Under this approach, each corrective maintenance (CM) event restores functionality but does not improve the underlying condition of the system. Expected failures per year f can be found with Equation 5.16.

$$f = \left(\frac{T - T_{\text{PM,year}} - f \cdot \text{MTTR}}{\eta'}\right)^{\beta'} \tag{5.16}$$

Here, T is the total annual operating time, $T_{\text{PM,year}}$ is the total planned preventive maintenance downtime, η' and β' are the adjusted Weibull parameters incorporating the effects of imperfect maintenance, and MTTR denotes the mean time to repair for unplanned corrective actions. This equation needs to be solved iteratively with damping for numerical stability.

Operational availability can be computed with Equation 5.17.

$$A = 1 - \frac{T_{\text{PM,year}}}{T} - \frac{f \cdot \text{MTTR}}{T}, \tag{5.17}$$

This formulation therefore integrates both planned and unplanned downtime.

5.4.2. Operator

In the complete model, operator availability is a critical factor in terminal performance, influencing the operational readiness of QC, HT, and YC. In the model, operator availability is primarily determined by two factors: the terminal shift and the presence of labor strikes.

The node 'Shift' captures the time of day during which operations occur, discretized into two levels: Day and Night. Based on typical operational patterns, these states are assigned probabilities of 0.6

and 0.4, respectively. The node 'Strike' models the occurrence of labor strikes, with states 'No' and 'Yes'. The labor strike node has probabilities of 0.95 and 0.05, respectively, reflecting the infrequency of strike events.

Each equipment subsystem has a dedicated operator availability node, which depends on the 'Shift' and 'Strike' nodes. This allows the model to account for the different criticality and staffing requirements of each subsystem.

Quay Crane Operators QC operations depend on highly specialized personnel, and even short-term unavailability affects the performance. The conditional probabilities reflect this high criticality, with a sharp reduction in operator availability during strikes or uncovered shifts. The conditional probabilities for 'Operator Availability QC' are summarized in Table 5.9.

Table 5.9: Conditional probabilities for 'Operator Availability QC' based on Shift and Strike

Parent Nodes		Operator Availability QC		
Shift	**Strike**	**High**	**Medium**	**Low**
Day	No	0.90	0.10	0.00
Night	No	0.85	0.15	0.00
Day	Yes	0.00	0.00	1.00
Night	Yes	0.00	0.00	1.00

Horizontal Transport Operators HT operations are less dependent on specialized labor, and shift or strike effects are therefore slightly less pronounced. The conditional probabilities for 'Operator Availability HT' are provided in Table 5.10.

Table 5.10: Conditional probabilities for 'Operator Availability HT' based on Shift and Strike

Parent Nodes		Operator Availability HT		
Shift	**Strike**	**High**	**Medium**	**Low**
Day	No	0.95	0.05	0.00
Night	No	0.90	0.10	0.00
Day	Yes	0.00	0.00	1.00
Night	Yes	0.00	0.00	1.00

Yard Crane Operators YC operators have intermediate criticality in terms of operators. YC operator unavailability impacts operations more than HT but less than QC. The CPD capturing this moderate sensitivity is provided in Table 5.11.

Table 5.11: Conditional probabilities for *Operator Availability YC* based on Shift and Strike

Parent Nodes		Operator Availability YC		
Shift	**Strike**	**High**	**Medium**	**Low**
Day	No	0.95	0.05	0.00
Night	No	0.90	0.10	0.00
Day	Yes	0.00	0.00	1.00
Night	Yes	0.00	0.00	1.00

Effective availability for each subsystem is calculated as the minimum of equipment availability and operator availability, ensuring that operations cannot exceed the capability of the least available component. This approach represents a conservative yet realistic assumption, as the absence of either functional equipment or personnel immediately limits subsystem performance.

6

Bayesian Network Analysis

This chapter presents an analysis of terminal performance using the constructed Bayesian Network (BN), which captures the causal relationships and conditional dependencies between environmental factors, equipment reliability, operator availability, and subsystem interactions. By leveraging the probabilistic structure of the BN, it is possible to estimate the likelihood of different delay outcomes and assess the potential impact of hypothetical interventions on terminal operations.

Two complementary approaches are applied in this study: forward inference and sensitivity analysis. Forward inference propagates known input conditions—such as weather, equipment state, and storage utilization—through the BN to compute posterior probabilities of subsystem and total terminal delays. Sensitivity analysis quantifies the influence of individual nodes on these outcomes, highlighting which factors most strongly affect terminal performance. Both the base and complete BN models are analyzed to illustrate the effects of different operational assumptions.

The analysis focuses on understanding how variations in equipment reliability, environmental conditions, maintenance, and operator availability influence overall delay risk at the terminal. This allows a detailed examination of how different conditions propagate through the network and affect subsystem dependencies and overall delay behavior.

The BN was implemented in Julia using the BayesNets.jl package (Stanford Intelligent Systems Laboratory (SISL), 2025), allowing efficient scenario testing and applying inference methods. The complete code is provided at https://github.com/ececoksayar/Graduation-assignment-BN-code- for transparency and reproducibility.

6.1. Introduction to Inference Methods

This section introduces the analytical approaches used to extract insights from the BN. By applying forward inference and sensitivity analysis, it is possible to quantify how variations in input factors propagate through the network and affect subsystem and total terminal delays. Forward inference predicts the likelihood of delay outcomes under specific scenarios, while sensitivity analysis identifies which factors have the greatest influence on overall performance.

6.1.1. Forward inference

Forward inference estimates the probability of specific outcomes based on known input conditions. This is useful for scenario simulation and forecasting, as it propagates evidence through the BN to update the likelihood of downstream outcomes such as subsystem delays or total terminal delay. Forward inference allows for the prediction of system behavior under different hypothetical conditions, enabling planning, risk assessment, and operational decision-making. In the context of this study, forward inference is used to simulate how environmental factors (e.g., weather), equipment status (e.g, age), and operational conditions (e.g., storage level) contribute to total system delay and its intermediate causes.

The forward inference process involves conditioning the network on known states of input nodes (such as weather, equipment availability, and storage capacity) and performing a Monte Carlo simulation with many runs to estimate posterior probability distributions for downstream nodes. In this study, one million samples were used. This sample size was chosen to ensure statistical stability of posterior probabilities while keeping computation time manageable. Each sample is then filtered to match the specified evidence, and the relative frequency of Low, Medium, and High delays is computed for each subsystem and the total terminal delay. This approach captures the stochastic variability inherent in equipment performance, environmental conditions, and subsystem interactions, which explains why rare high-delay events may still occur even under optimal input conditions.

The outputs of forward inference can be summarized in tables or visualized using stacked bar charts. This not only facilitates interpretation of how changes in individual inputs or combinations of inputs affect subsystem and total delays, but also serves as a sanity check to ensure that the BN produces results consistent with domain knowledge and operational expectations, helping to validate that the model is working correctly.

6.1.2. Sensitivity Analysis

Sensitivity analysis evaluates how variations in a specific input node affect the probability distribution of a target node, such as total terminal delay. In this study, each input node was varied individually by conditioning on a specific value, while all other nodes were left unconstrained and sampled according to their prior distributions in the BN. This approach isolates the effect of the selected node on subsystem and total delays, while still accounting for probabilistic variability in the rest of the system.

For each input scenario, the Bayesian Network is sampled repeatedly using Monte Carlo simulation (100,000 samples per scenario). For each sample, the states of the delay nodes — Quay Crane (QC) Delay, Horizontal Transport (HT) Delay (Empty and Loaded), Yard Crane (YC) Delay, and Total Delay — are recorded. The expected value of each delay node is then computed from the posterior distribution by taking a weighted sum over the discrete states (Low = 1, Medium = 2, High = 3). These expected values are presented as percentages of Low, Medium, and High delays for each scenario. By comparing these values across different input scenarios, the analysis quantifies the marginal influence of each input node on subsystem and total terminal delays, highlighting the factors that most strongly affect system performance.

This type of analysis is particularly useful for prioritizing interventions or operational monitoring. By identifying which single factors have the largest effect on terminal performance, sensitivity analysis can indicate where targeted improvements—such as maintenance schedules, staffing adjustments, or operational policies—would likely produce the most significant gains in reliability and efficiency.

6.2. The Base Model

The base BN serves as a reference framework for analysing the reliability and delay propagation within the terminal system under typical operating conditions. In this simplified model, equipment reliability is represented solely through age-dependent Weibull-based failure probabilities. Environmental conditions (wind, rain, and visibility) together with operational factors (terminal busyness and yard storage utilization) determine subsystem operability and efficiency. Preventive maintenance interventions and operator availability are not included at this stage, allowing the analysis to focus on the inherent behavior of the system components and their interactions.

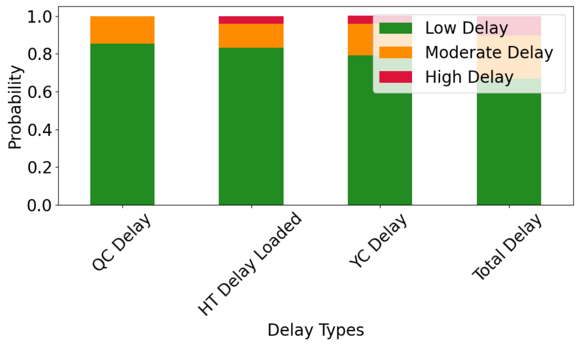
This baseline scenario establishes the foundation for understanding how delays arise naturally from subsystem performance and environmental factors. It enables the quantification of the impact of weather, equipment age, and basic operational constraints influence delay formation and propagation across subsystems. The results provide a benchmark against which the effects of additional interventions, such as maintenance or staffing variations, can later be evaluated. The following sections present detailed analyses of weather sensitivity, equipment reliability, availability, terminal state, and delay propagation using this base BN.

6.2.1. Forward Inference

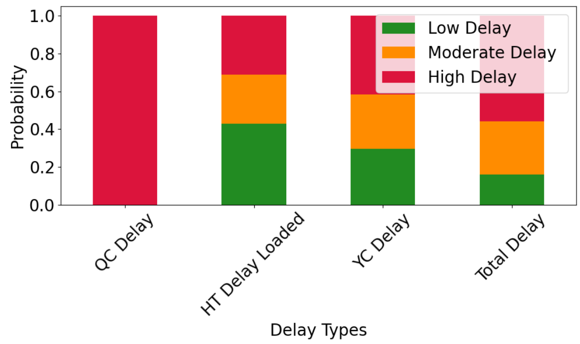
Forward inference was applied to the base BN to evaluate the effect of different operational scenarios on subsystem and total terminal delays. Initially, an optimal scenario was examined, in which weather conditions were mild (low wind, no rain, high visibility), storage capacity was sufficient, and all equipment subsystems (QC, YC, HT) were in the high availability bins. Posterior distributions of subsystem delays and total delay were computed by conditioning the network on these inputs, allowing the probability of Low, Medium, and High delays to be assessed. This 'Optimal Scenario' establishes a reference distribution of subsystem and total delays, providing a benchmark against which other, less favorable conditions can be compared.

To illustrate the sensitivity of the terminal to adverse conditions, three additional scenarios were analyzed, each varying only a single input node while keeping all other conditions at baseline. In the 'Severe Wind Scenario', only wind was increased to 'high' to simulate strong wind conditions, demonstrating how environmental constraints alone can propagate through the network and elevate the probability of High delays. In the 'Low HT Availability' Scenario, the availability of HTs was reduced to represent aging equipment or operational faults, highlighting the sensitivity of subsystem and total delays to equipment reliability. Finally, in the 'Low Storage Capacity Scenario', terminal storage utilization was constrained to a low-availability state, showing how limited yard space affects YC performance and contributes to total delay.

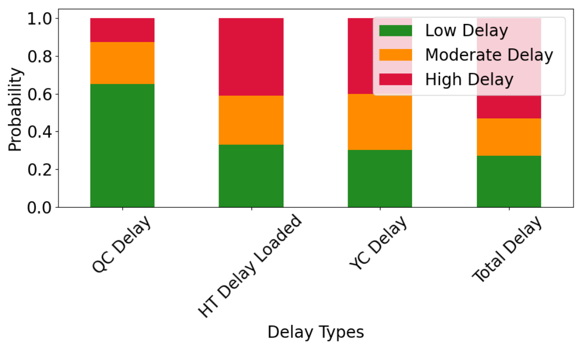
Figure 6.1 shows a stacked bar chart summarizing the delay probabilities for the QC, HT, and YC subsystems, as well as the total delay for the given scenarios.



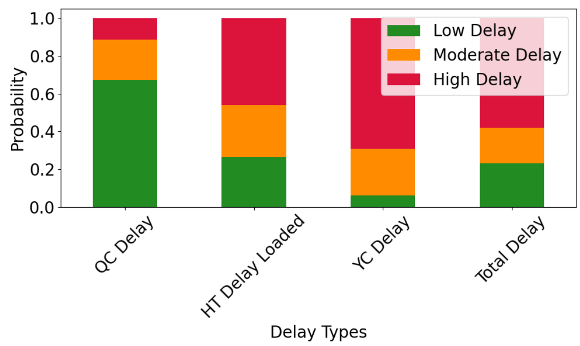
(a) Delay Distribution for the Optimal Scenario



(b) Delay Distribution for the Severe Wind Scenario



(c) Delay Distribution for the Low HT Availability Scenario



(d) Delay Distribution for the Low Storage Capacity Scenario

Figure 6.1: Probability distributions of subsystem and total delays for different scenarios

In the 'Optimal Scenario' shown in Figure 6.1a, 96 out of 1,000,000 samples matched the evidence. The majority of the simulations produced low delays across all subsystems, reflecting smooth terminal operations. However, a small fraction of samples still resulted in medium or high delays. This occurs because the BN captures stochastic variability and inherent uncertainty in subsystem interactions, such as random repair times and high availability bin including a range rather than only 100%. Even under optimal input conditions, these random factors can propagate through the network, occasionally producing higher-than-expected delays, illustrating the non-deterministic nature of terminal operations and highlighting the importance of probabilistic modelling for reliability assessment.

In the 'Severe Wind Scenario' shown in Figure 6.1b, extreme wind conditions primarily disrupt quay crane operations. Out of one million samples, only 2,999 samples matched this high-wind evidence. However, in those cases, high QC delays were observed due to QC not being able to operate under severe wind conditions, which substantially increased the total terminal delay. The 'Low HT Availability Scenario' shown in Figure 6.1c gave similar results with 406,155 samples matching the conditioned low-availability evidence. Low HT availability increases the delay for the HT subsystem, which also causes a slight increase in the QC subsystem due to QCs waiting for HTs.

Finally, in the 'Low Storage Capacity Scenario' given in Figure 6.1d, 400,525 samples matched the evidence. In these simulations, YC delays increased substantially due to congestion, which in turn propagated to HT delays, particularly for loaded HTs, as containers could not be offloaded efficiently. This cascading effect amplified total terminal delay, illustrating how limited storage capacity can drastically affect YC operations and indirectly increase HT delays, ultimately impacting overall system performance.

6.2.2. Delay Propagation through Subsystems

Delay propagation through subsystems is examined to understand how local slowdowns spread through the terminal. In this analysis, the delay level of one subsystem at a time (HT-Empty, HT-Loaded, YC, or QC) is fixed to medium or high, while all other nodes remain at their baseline distribution. The baseline in this subsection represents the average state of the system without additional evidence. This baseline does not correspond to a perfect or "ideal" condition, but rather to the expected performance of the terminal under typical operating circumstances. By comparing this baseline with scenarios in which a single delay node is elevated, the model demonstrates how congestion in an individual subsystem propagates through the network and influences the overall terminal delay. This analysis highlights the relative importance of each subsystem in contributing to network-wide performance losses. The effect of subsystem delays on the total delay can be visualized in Figure 6.2.

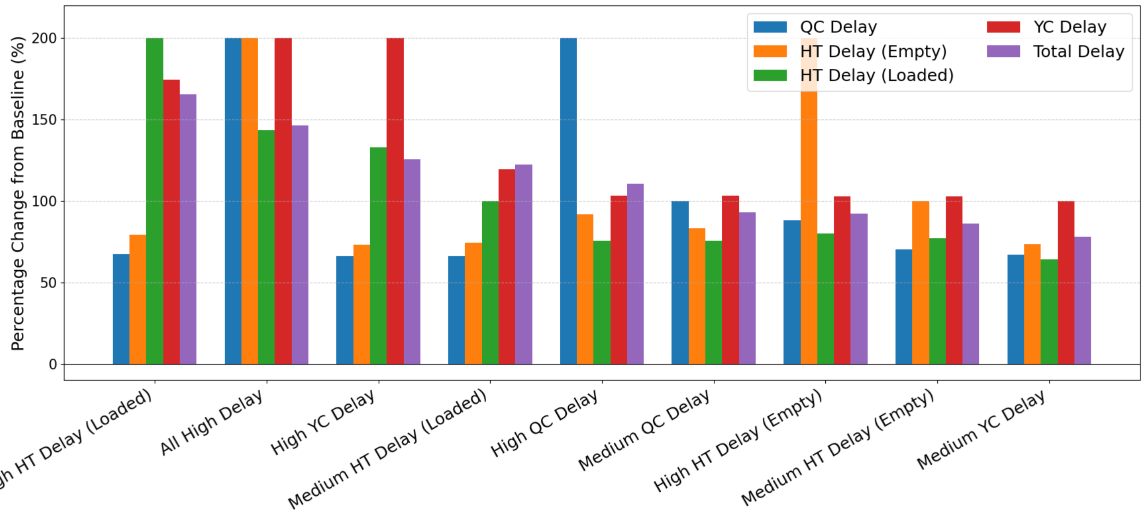


Figure 6.2: Delay Propagation through Subsystems

The results show important interactions between subsystems. When the HT (Empty) delay increases, the QC delay rises in parallel, since QCs depend on the timely supply of empty vehicles to continue operations. This illustrates the coupling between quay and horizontal transport at the seaside interface. Similarly, when YC delay increases, the effect is transmitted directly into HT (Loaded) delay, as yard-side congestion restricts the turnaround of loaded vehicles.

The results also underline the significance of subsystem delays for overall terminal performance. Each component contributes to congestion at the system level, but the strength of the effect varies. HT (Loaded) has the strongest impact on total delay, reflecting its role as the key link between quay operations and the yard. YC delays follow closely, as they directly increase HT (Loaded) delays and reinforce landside congestion.

QC delays are also substantial, but their influence on terminal-wide delay is weaker than that of HT and YC. While QC delay levels themselves can rise considerably, their effect on total delay is moderated by the structure of the BN. QC feeds into the system through a single pathway (through QC delay), whereas HT and YC affect several dependent nodes simultaneously, explaining their stronger overall impact on terminal performance.

6.2.3. Weather Sensitivity

In the BN model, weather has an impact on the QC subsystem. To assess these effects, several weather scenarios were defined and compared to a baseline condition of no wind, no rain, and high visibility. The scenarios include varying wind speeds (moderate to strong), different levels of rainfall (light to heavy), and changes in visibility (moderate to low). In each scenario, only the specified weather variable is conditioned, while the remaining weather nodes are left unconstrained and sampled according to their prior distributions. This approach isolates the marginal effect of each weather factor on terminal performance while preserving the natural variability of other environmental conditions. An additional "Severe Weather" scenario combines strong wind and heavy rain to represent extreme conditions. The relative impact of each weather condition on QC and total delays is shown in Figure 6.3.

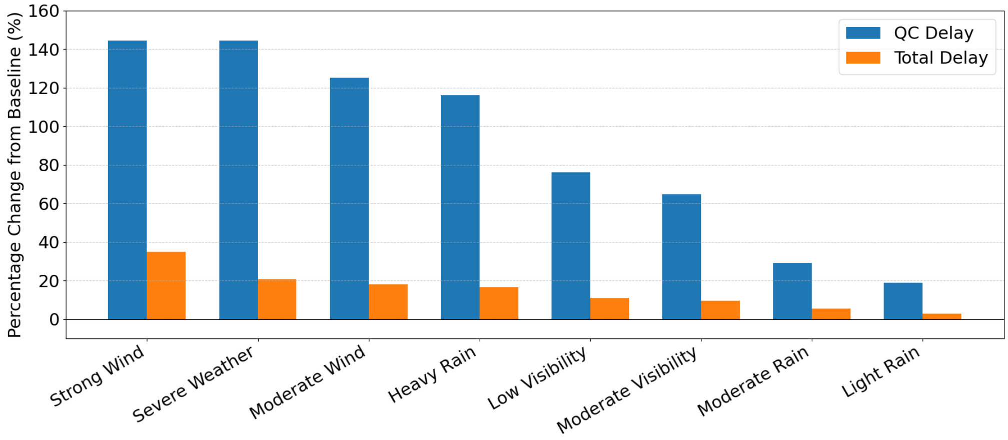


Figure 6.3: Weather Sensitivity

The results show that wind is the dominant weather factor influencing terminal performance. Under strong wind and severe weather conditions, QC operations slow down sharply, leading to a noticeable rise in overall terminal delays. Even moderate wind produces a visible increase, confirming that QC operability is highly sensitive to wind conditions. In comparison, the influence of rain and visibility is more modest. Heavy rain and low visibility lead to some increase in QC delay, but their effect on overall terminal delay remains limited. Moderate or light rain and visibility changes have only minor consequences.

Overall, the sensitivity analysis indicates that terminal-wide performance is governed mainly by wind-driven interruptions of QCs, whereas rain and visibility play a secondary role, reducing efficiency but not stopping operations. Interestingly, the increase in total delay under severe weather is smaller than might be expected. This occurs because such extreme wind events are rare in the sampled data, and in those cases, other subsystems, such as horizontal transport, are not always simultaneously congested. As a result, the impact of quay crane stoppages on total terminal delay is partially absorbed by the probabilistic interactions across subsystems.

6.2.4. Equipment Reliability

In the base model, the availability of critical equipment is directly influenced by its age, with older equipment having higher failure rates. As equipment ages, both the Mean Time Between Failures (MTBF) and the availability of the equipment decreases. This is captured in the Weibull distribution, used to model failure rates, where older equipment experiences more frequent failures.

Figure 6.4 illustrates the cumulative failure distributions (CDFs) for QC, HT, and YC subsystems across different equipment ages. The curves clearly show how aging shifts the probability of failure toward earlier times: new equipment has a slower rise in cumulative probability, while mid-life and old equipment experience much steeper increases, reflecting higher failure likelihoods and shorter expected lifetimes.

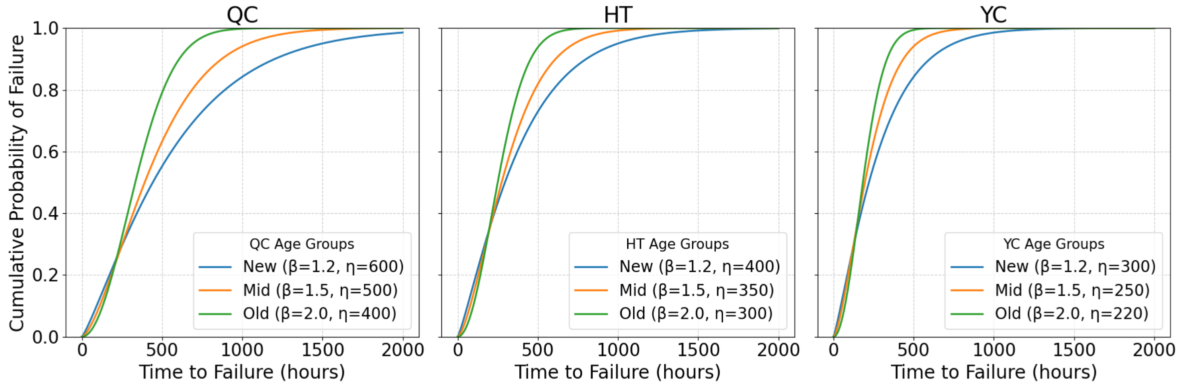


Figure 6.4: Cumulative Probability of Failure of Equipment

Table 6.1 shows the relationship between equipment age (New, Mid, Old) and expected availability for QC, HT, and YC subsystems. It also includes the Weibull parameters used, the MTBF calculated, and the MTTR values used to compute availability. New equipment shows higher availability, reflecting lower failure likelihood and shorter repair times, while older equipment exhibits significantly lower availability, with failure rates more pronounced and longer total repair times. To integrate these continuous availability values into the Bayesian Network, the availability is discretized into three operational states—Low, Medium, and High—using smoothed thresholds defined in Equation 5.7.

Subsystem	Age	β	η	MTBF (h)	MTTR (h)	Mean Avail. (%)	Low (%)	Medium (%)	High (%)
QC	New	1.2	600.0	564.39	24.66	95.81	0.00	79.67	20.33
	Mid	1.5	500.0	451.37	24.66	94.82	0.00	100.00	0.00
	Old	2.0	400.0	354.49	24.66	93.50	12.62	87.38	0.00
YC	New	1.2	300.0	282.20	14.39	95.15	0.00	96.27	3.73
	Mid	1.5	250.0	225.69	14.39	94.01	0.00	100.00	0.00
	Old	2.0	220.0	194.97	14.39	93.13	21.80	78.20	0.00
HT	New	1.2	400.0	376.26	8.22	97.86	0.00	53.45	46.55
	Mid	1.5	350.0	315.96	8.22	97.46	0.00	63.40	36.60
	Old	2.0	300.0	265.87	8.22	97.00	0.00	74.98	25.02

Table 6.1: Reliability and availability parameters for each subsystem and age group

Figure 6.5presents the distribution of availability states (Low, Medium, High) for QC, HT, and YC subsystems across different equipment ages. The results show that as equipment ages, the proportion of units in the high availability state decreases, while low availability state increases.

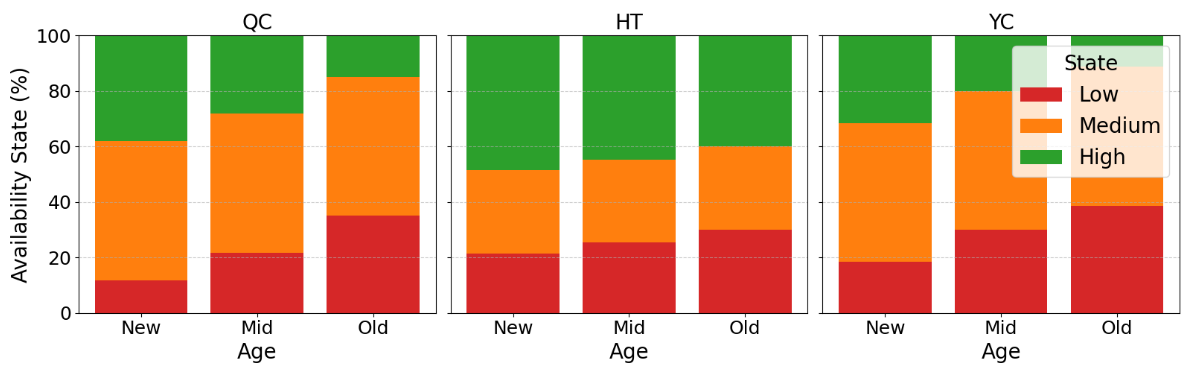


Figure 6.5: Availability State Distribution by Age

6.2.5. Availability Sensitivity

The subsystem delays and total terminal delays are influenced by the availability of its critical equipment. This analysis evaluates how reductions in equipment availability affect subsystem performance and the propagation of delays through the terminal network. The baseline scenario is determined to have high availability for all types of equipment. For the other scenarios, only one subsystem's availability is altered at a time, while the others remain fixed at high availability. The effect of equipment availability on subsystem delays and the total delay is visualized in Figure 6.6.

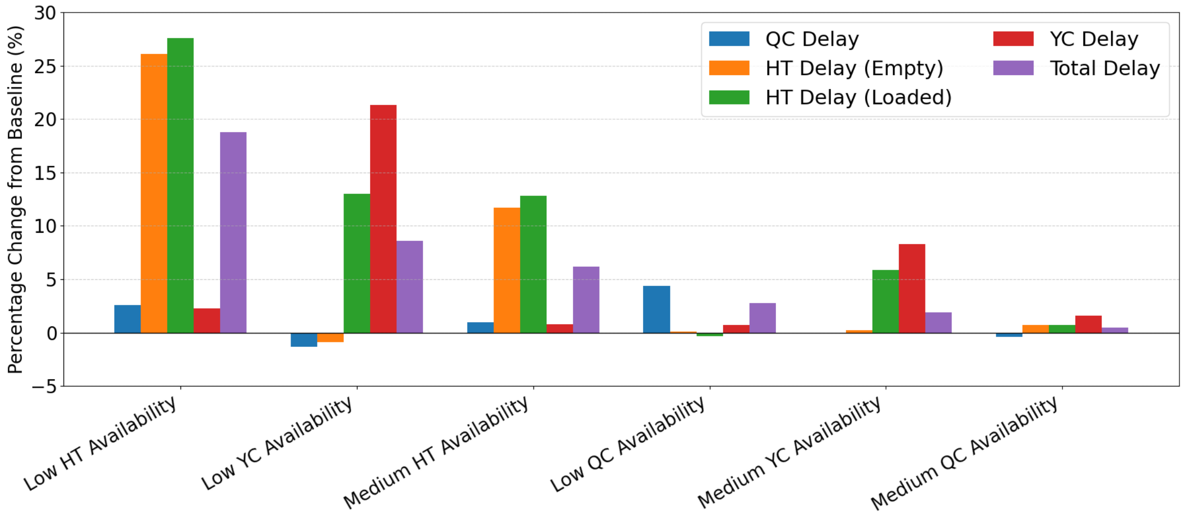


Figure 6.6: Equipment Availability Sensitivity

The sensitivity analysis demonstrates that equipment availability has a clear influence on subsystem delays and overall terminal performance. Among the subsystems, HT availability shows the strongest effect. Under low availability, both HT delays rise sharply, leading to a noticeable increase in total delay. Even under medium availability, HT delays remain elevated. YC availability also shows a significant effect, particularly on its own subsystem. Low YC availability increases YC delays significantly and also amplifies HT (Loaded) delays, but its effect on total delay remains more moderate. Medium YC availability produces a smaller rise in subsystem delays and a limited overall effect.

In contrast, QC availability shows only a modest influence. Low QC availability slightly increases QC delays, but its effect on total delay is minimal and in some cases even slightly negative. This reflects both the BN structure and the probabilistic interactions between subsystems. QC availability affects only the QC delay node, while HT and YC availability influence several nodes simultaneously. In addition, in some samples, lower QC availability coincides with relatively favorable HT or YC conditions, partially offsetting its impact at the terminal level. HT availability dominates because it connects the two critical operational areas and acts as a bottleneck when capacity is reduced.

6.2.6. Terminal Situation Sensitivity

Terminal state variables such as yard storage capacity and terminal busyness determine how efficiently containers can be transferred between subsystems under varying workload and space constraints. Analyzing their influence helps to understand how congestion and yard utilization affect delay propagation through the terminal. Figure 6.7 shows the sensitivity of terminal delays to different operational conditions, including busyness levels and storage availability, relative to the baseline scenario. Baseline scenario used in this case is low terminal busyness and high storage availability. Visualization of the results can be found in Figure 6.7.

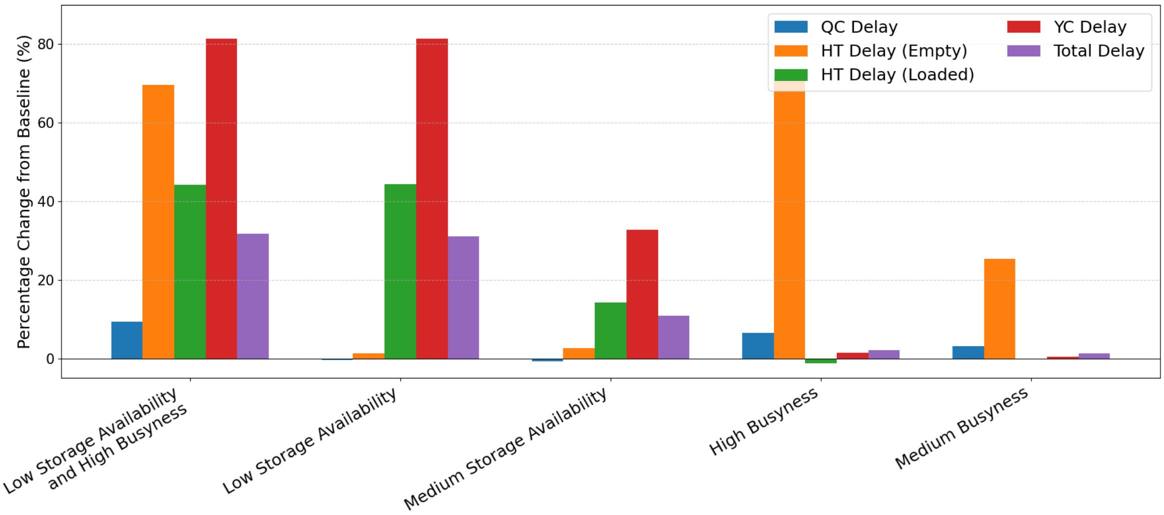


Figure 6.7: Terminal State Sensitivity

The results show that storage availability is the most critical factor among the terminal state variables. When storage capacity is reduced, it introduces a significantly high YC delay. Due to the YC and HT interaction, this situation also increases HT delay (Loaded). This combination leads to a clear rise in overall terminal delay. Under medium storage conditions the effect is still visible, though less severe, while the worst-case scenario of low storage and high busyness produces the strongest disruption across the system.

Increasing the terminal busyness has a significant impact on the HT delay empty, which also causes a delay in the QC subsystem. However, these effects remain largely localised and do not translate into a substantial increase in terminal-wide delay. Even at elevated levels of busyness, the effect on overall performance is limited compared with the impact of storage shortages.

6.2.7. Sensitivity Analysis

For the sensitivity study, a universal baseline scenario was defined in which all input variables were set to their best-case states: favorable weather (low wind, no rain, high visibility), low terminal busyness, sufficient storage capacity, and high availability of QC, YC, and HT. This baseline serves as a reference point for measuring relative changes in delay outcomes.

To assess the impact of each factor, scenarios were defined by fixing the corresponding BN node to a specific state, while leaving all other nodes free to vary according to their conditional probability distributions. This approach captures the individual effect of each variable on total terminal delay while allowing the probabilistic dependencies among other factors to remain active.
The combined sensitivity results identify wind, storage availability, and HT availability as the most influential factors driving terminal performance. Among all variables, strong wind has the strongest impact, producing the largest increase in total delay. This underlines the vulnerability of QC operability to severe wind conditions, which can directly suspend operations. Low storage availability also ranks near the top, demonstrating how yard-side constraints quickly propagate through the network and restrict container flows. Low HT availability is the most critical equipment-related factor, as it has impact on both quay-side and yard-side operations.

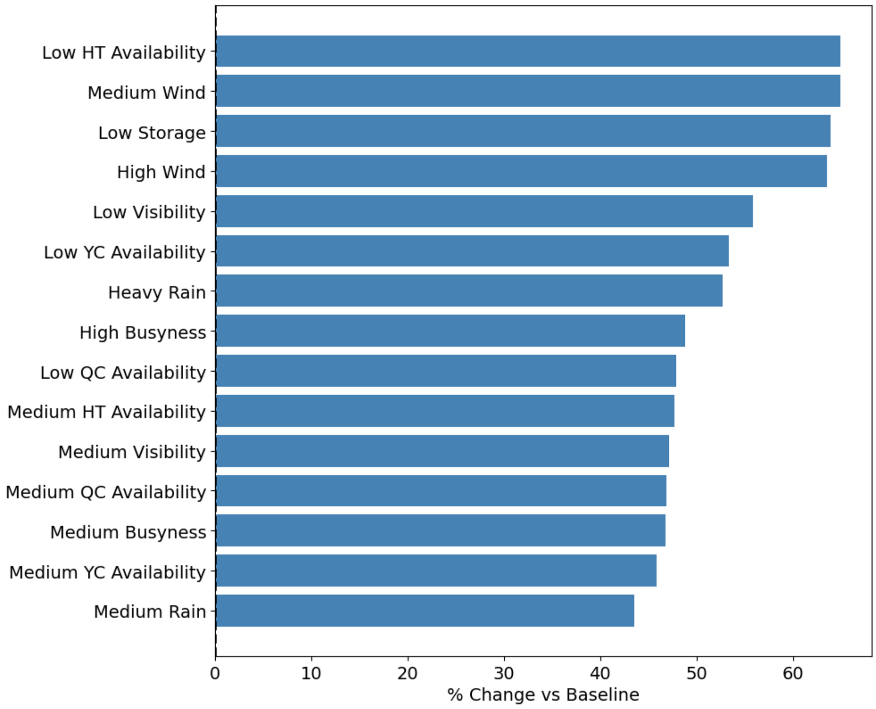


Figure 6.8: Combined Sensitivity Results for the base terminal

6.3. Complete Model

The complete BN model extends the base reliability structure by integrating both operator and maintenance related components, which represent the two main controllable dimensions of terminal performance. While the baseline model captures the inherent reliability of equipment and its dependencies on environmental conditions, the complete model introduces the capacity to evaluate how human performance and maintenance strategies jointly influence system availability and delay propagation.

In this section, the effects of operator behavior and preventive maintenance policies are analyzed separately to illustrate their respective contributions to overall terminal reliability.

6.3.1. Operator Effect

The operator-related nodes were introduced to capture human performance variability and its influence on the terminal's overall reliability and delay behavior. For the sensitivity analysis, the day shift without strike scenario was used as the baseline reference, representing normal operating conditions.

During strike events, operator availability is automatically set to unavailable, regardless of whether the event occurs during day or night, effectively representing a complete shutdown of human-operated activities. Conversely, during regular night operations, operator availability is slightly reduced compared to the day shift, reflecting the possible availability differences between shifts. This effect is most pronounced for quay crane (QC) operations, where operator availability plays a critical role due to the need for highly specialized and certified personnel.

The resulting impact of these scenarios on subsystem and total delays is summarized in Table 6.2, where the strike and night conditions are compared against the baseline.

Table 6.2: Scenario-based delay comparison relative to baseline.

Scenario	QC Delay (%)	YC Delay (%)	HT Delay Loaded (%)	Total Delay (%)
Strike	+111.8	+110.2	+159.4	+108.3
Night	+6.3	+0.2	-0.2	+1.8
Baseline	+0.0	+0.0	+0.0	+0.0

The results indicate that strike conditions have a drastic impact across all operational layers, with total delays more than doubling relative to the baseline. This reflects the complete unavailability of operators and the resulting halt in equipment utilization. In contrast, night operations produce only marginal increases in delay, mainly driven by slightly lower operator availability and slower coordination between subsystems.

6.3.2. Maintenance Effect

Preventive maintenance (PM) portfolios were developed to examine how different combinations of maintenance types and frequencies influence equipment reliability and terminal availability. Three levels of maintenance intensity were considered: Minor, Medium, and Major, each corresponding to progressively deeper restorative effects. Each type was evaluated under multiple frequency regimes (none, weekly, monthly, and yearly), and several combined portfolios were designed to represent realistic maintenance practices.

The tested portfolios include single-frequency strategies as well as more realistic combined policies. These combinations allow for the comparison of short-cycle preventive maintenance routines against longer-term overhaul-based policies. This analysis provides insight into how different maintenance planning strategies affect overall terminal reliability and delay propagation within the complete BN model.

Maintenance effect in QC Table 6.3 summarizes the resulting reliability metrics for all maintenance portfolios for QC, including the expected parameter multipliers (E_η, E_β), mean time between failures (MTBF), mean time to repair (MTTR), and resulting availability.

Table 6.3: Maintenance Portfolio Results for QC

Portfolio	E_η	E_β	MTBF [h]	MTTR [h]	Availability
No PM	0.000	0.000	454.552	24.440	0.823
Minor Weekly	0.367	0.199	732.902	24.411	0.907
Minor Monthly	0.100	0.050	507.882	24.710	0.843
Minor Yearly	0.009	0.004	458.876	24.516	0.824
Medium Weekly	0.713	0.506	2277.457	24.518	0.951
Medium Monthly	0.250	0.150	656.707	24.722	0.889
Medium Yearly	0.024	0.013	469.299	24.569	0.827
Major Weekly	0.981	0.787	26377.657	24.788	0.857
Major Monthly	0.600	0.300	1176.962	24.722	0.929
Major Yearly	0.074	0.029	491.853	24.762	0.834
Minor Weekly + Major Yearly	0.413	0.223	788.893	24.658	0.912
Minor Monthly + Major Yearly	0.166	0.078	550.105	24.459	0.858
Medium Monthly + Major Yearly	0.305	0.175	711.157	24.429	0.899
Minor Weekly + Medium Monthly	0.525	0.319	1059.268	24.675	0.935
Minor Weekly + Medium Monthly + Major Yearly	0.560	0.339	1147.658	24.910	0.938

Figure 6.9 shows the breakdown of yearly downtime for each maintenance strategy applied to the quay cranes, highlighting how preventive maintenance reduces corrective downtime at the cost of additional planned maintenance hours.

For the QCs, the baseline scenario without preventive maintenance (No PM) showed an availability of 82.3%. This corresponds to about 1,569 hours of corrective downtime per year, which is around 18% of the total operational time. Implementing preventive measures greatly improves performance. The 'Medium Weekly' strategy achieved the highest availability of 0.951, cutting corrective downtime to just 118 hours per year. This is a reduction of more than 1,100 hours compared to the baseline. The improvement comes from both fewer failures (around five per year) and the benefits of regular maintenance, despite the additional 312 hours of planned downtime per year.

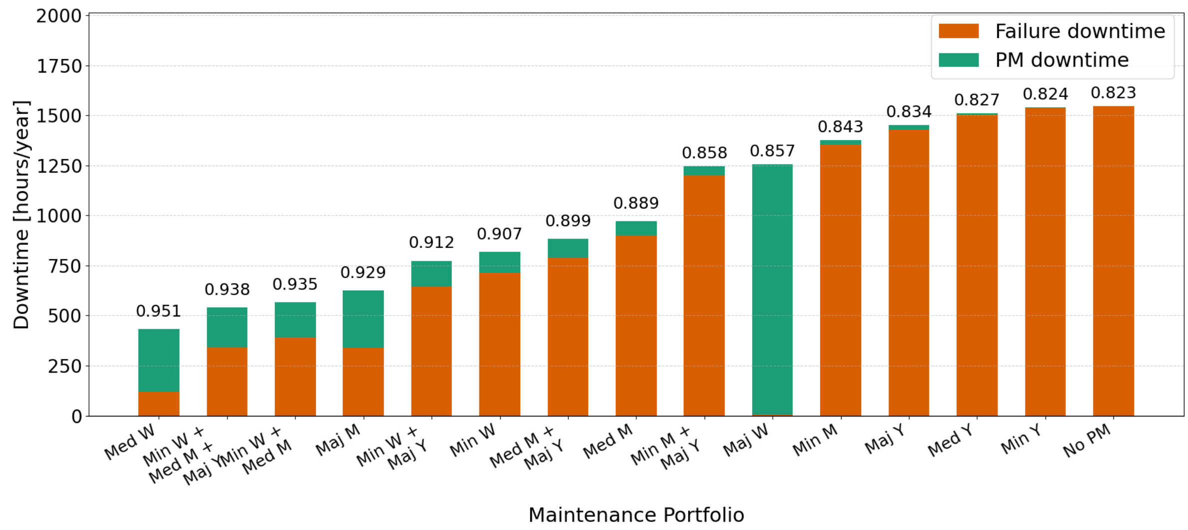


Figure 6.9: Downtime Breakdown for QC

Moderate strategies offer the best efficiency in terms of downtime saved per hour of maintenance. For example, 'Minor Weekly' (104 hours of PM annually) increased availability to 90.7%, lowering total downtime to 826 hours. Meanwhile, 'Minor Weekly + Medium Monthly' (176 hours of PM) achieved 93.6% availability with only 561 hours of total downtime. These plans save about 6-7 hours of total downtime for each hour of preventive maintenance, making them the most balanced and cost-effective options. Adding 'Major Yearly' maintenance to this mix results in a slight additional gain (availability 93.8%) for a small increase in PM hours (up to 200). In contrast, 'Major Weekly'—which includes 1,248 hours of planned downtime per year—resulted in only 85.7% availability. Although the number of failures dropped nearly to zero, the heavy PM workload outweighed the benefits. This shows clear over-maintenance and suggests that major interventions should follow annual schedules. Overall, the results show that frequent minor and medium maintenance actions provide the highest availability gains with optimal efficiency, while excessive major maintenance quickly becomes counterproductive.

Maintenance effect in HT Table 6.4 summarizes the resulting reliability metrics for all maintenance portfolios for HT, including the expected parameter multipliers (E_η, E_β), mean time between failures (MTBF), mean time to repair (MTTR), and resulting availability.

Table 6.4: Maintenance Portfolio Results for HT

Portfolio	E_η	E_β	**MTBF [h]**	**MTTR [h]**	**Availability**
No PM	0.000	0.000	317.267	8.206	0.869
Minor Weekly	0.367	0.199	510.788	8.186	0.943
Minor Monthly	0.100	0.050	354.889	8.238	0.893
Minor Yearly	0.009	0.004	320.774	8.297	0.870
Medium Weekly	0.713	0.506	1592.706	8.162	0.981
Medium Monthly	0.250	0.150	459.903	8.226	0.932
Medium Yearly	0.024	0.013	327.995	8.182	0.875
Major Weekly	0.981	0.787	18515.115	8.286	0.976
Major Monthly	0.600	0.300	816.066	8.191	0.971
Major Yearly	0.074	0.029	343.572	8.170	0.885
Minor Weekly + Major Yearly	0.413	0.223	552.488	8.187	0.949
Minor Monthly + Major Yearly	0.166	0.078	383.535	8.364	0.905
Medium Monthly + Major Yearly	0.305	0.175	498.167	8.214	0.941
Minor Weekly + Medium Monthly	0.525	0.319	743.397	8.230	0.967
Minor Weekly + Medium Monthly + Major Yearly	0.560	0.339	802.465	8.193	0.969

Figure 6.10 shows the breakdown of yearly downtime for each maintenance strategy applied to the HT subsystem.

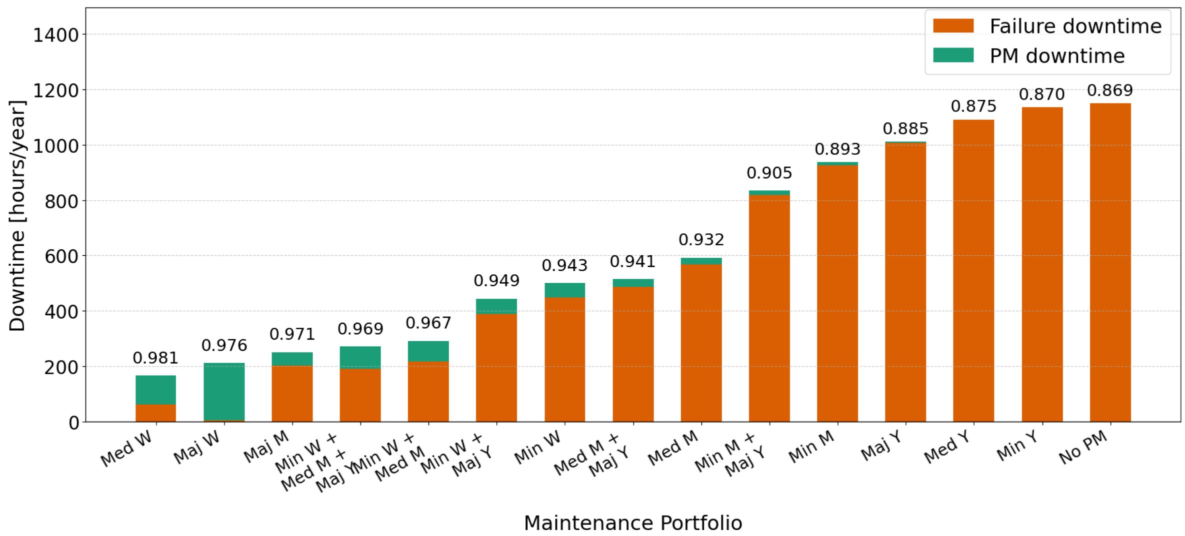


Figure 6.10: Downtime Breakdown for HT

For the HT subsystem, the baseline scenario without preventive maintenance (No PM) achieved an availability of 86.9%, which is about 1,149 hours of corrective downtime per year. This accounts for around 13.1% of the total operational time. The 'Medium Weekly' plan achieved the highest availability of 98.1%, reducing total downtime to only 166 hours per year, a cut of nearly 984 hours compared to the baseline, even though it required 104 hours of planned maintenance. This strategy also reduced the annual number of failures from about 104 to only 5 times.

Moderate preventive strategies deliver strong reliability gains with minimal maintenance effort. The Minor Weekly policy (52 hours of PM per year) increased availability to 94.3% and reduced total downtime to 500 hours, saving roughly 486 hours of lost time. Similarly, the Minor Weekly + Medium Monthly combination (156 hours of PM) boosted availability to 96.74% with 291 total downtime hours, providing a balanced trade-off between maintenance effort and reliability. The 'Major Weekly' policy, which includes 208 hours of PM annually, only slightly improved availability to 97.6% compared to lighter schedules, as the large maintenance workload offset most of the benefits.

Maintenance effect in YC Table 6.5 summarizes the resulting reliability metrics for all maintenance portfolios for YC, including the expected parameter multipliers (E_η, E_β), mean time between failures (MTBF), mean time to repair (MTTR), and resulting availability.

Figure 6.11 shows the breakdown of yearly downtime for each maintenance strategy applied to the YC subsystem.

For the YC subsystem, the scenario without preventive maintenance (No PM) resulted in an availability of 78.0%. This corresponds to about 1,926 hours of corrective downtime per year, which is roughly 22% of the total operating time. PM improves system performance, especially with medium-level policies. The 'Medium Weekly' plan achieved the highest availability of 94.7%. It reduced total downtime to just 466 hours per year, a decrease of about 1,460 hours from the baseline, despite adding 312 hours of planned maintenance.

Moderate maintenance strategies also perform effectively. The 'Minor Weekly' schedule, which includes 156 hours of preventive maintenance per year, improved availability to 86.5% and nearly halved total downtime to 1,180 hours. Similarly, the 'Medium Monthly' plan, with 72 hours of preventive maintenance, reached an availability of 0.85 and had 1,317 total downtime hours, achieving strong results with minimal added maintenance time. Combining 'Minor Weekly' and 'Medium Monthly' further raised availability to 91.4% while keeping downtime at a moderate level of 755 hours per year, making it one of

Table 6.5: Maintenance Portfolio Results for YC

Portfolio	E_η	E_β	MTBF [h]	MTTR [h]	Availability
No PM	0.000	0.000	230.537	14.438	0.780
Minor Weekly	0.367	0.199	371.110	14.470	0.865
Minor Monthly	0.100	0.050	257.982	14.491	0.804
Minor Yearly	0.009	0.004	233.000	14.391	0.784
Medium Weekly	0.713	0.506	1162.005	14.544	0.947
Medium Monthly	0.250	0.150	334.058	14.309	0.850
Medium Yearly	0.024	0.013	237.843	14.503	0.787
Major Weekly	0.981	0.787	13375.448	14.272	0.880
Major Monthly	0.600	0.300	593.276	14.327	0.916
Major Yearly	0.074	0.029	249.539	14.447	0.797
Minor Weekly + Major Yearly	0.413	0.223	400.162	14.496	0.876
Minor Monthly + Major Yearly	0.166	0.078	278.310	14.473	0.813
Medium Monthly + Major Yearly	0.305	0.175	360.888	14.394	0.863
Minor Weekly + Medium Monthly	0.525	0.319	538.469	14.352	0.914
Minor Weekly + Medium Monthly + Major Yearly	0.560	0.339	584.471	14.495	0.919

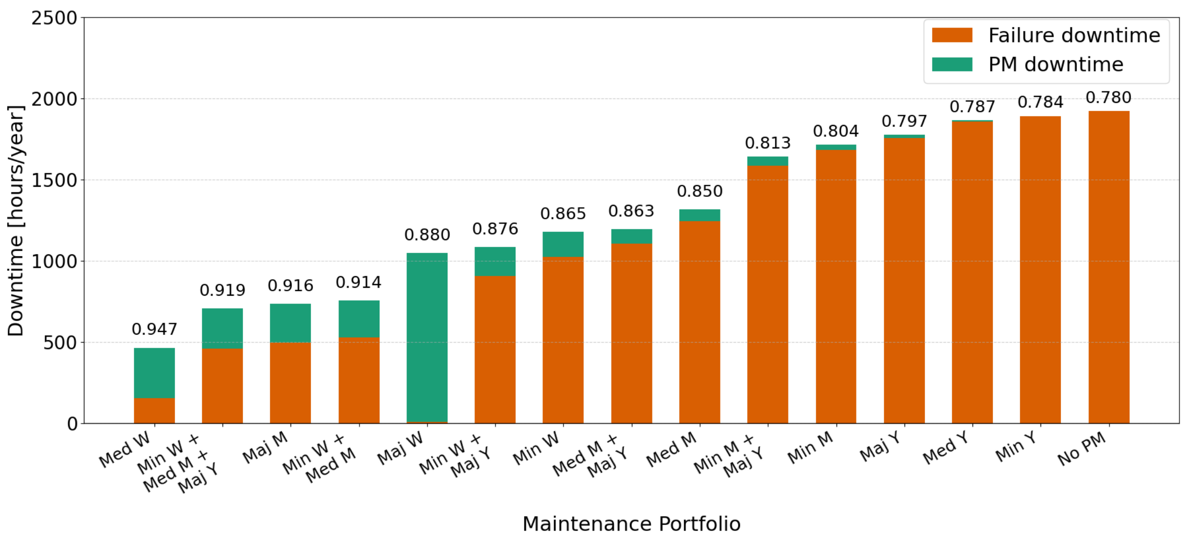


Figure 6.11: Downtime Breakdown for YC

the most cost-effective options. In contrast, the 'Major Weekly' maintenance plan, which requires 1,040 hours per year, did not yield any improvement. Availability fell to 88.0% with 1,048 h total downtime, as the excessive maintenance time outweighed the minor reduction in failures.

Comparative Analysis of PM Strategies Across all three subsystems, PM improved reliability and availability compared to the baseline no preventive maintenance scenario. However, the extent of improvement varied by equipment type. The QCs, with their long repair durations, showed the greatest response to preventive actions. In contrast, horizontal transport, which has a short mean time to repair, needed much less intervention to maintain high performance. In all systems, medium-frequency and mixed policies, such as Medium Weekly and Minor Weekly + Medium Monthly, provided the best balance between reduced failures and manageable preventive downtime. These strategies cut failure hours by more than half while keeping total preventive maintenance time under 5% of the operational year.

Nonetheless, the results also point to clear signs of over-maintenance. The 'Major Weekly' portfolios, while nearly eliminating failures, led to some of the lowest overall availabilities because the cumulative

PM time overshadowed the operating year.

Maintenance Effect on Total Delay To demonstrate how preventive maintenance influences terminal performance, the recalculated subsystem availabilities were propagated through the complete BN to estimate the resulting total delay. Table 6.6 summarizes the corresponding subsystem availabilities and improvement of delay compared to the no PM condition.

Table 6.6: PM strategy impact on terminal performance.

PM Strategy	QC Availability	YC Availability	HT Availability	Improvement
No Preventive Maintenance	82.2%	78.1%	86.7%	0.0%
Minor PM Weekly	90.5%	86.5%	94.2%	14.5%
Minor PM Monthly	84.0%	80.2%	89.4%	4.0%
Major PM Yearly	83.1%	80.0%	88.5%	3.2%
Comprehensive PM	93.9%	91.9%	96.9%	21.8%

Figure 6.12 illustrates the percentage reduction in total delay relative to the No Preventive Maintenance baseline.

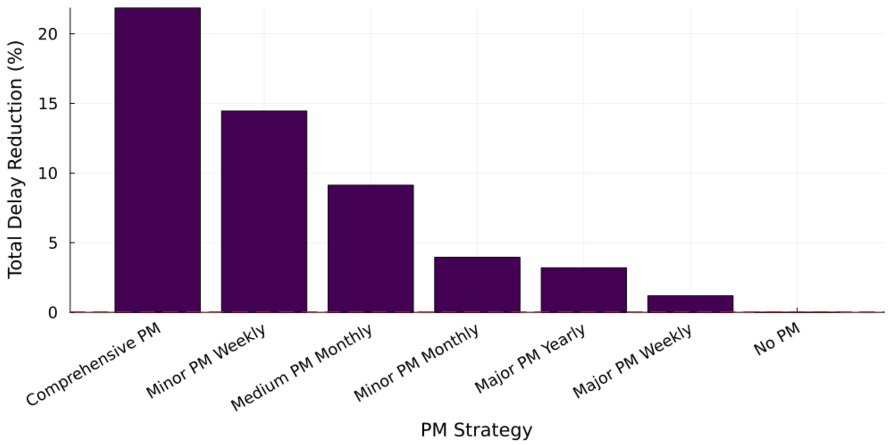


Figure 6.12: PM Strategy Percentage Improvement

The results show that increasing maintenance intensity generally improves subsystem availability and reduces total delay, although higher levels of interventios are not as effective. The 'Comprehensive PM' portfolio combines minor, medium, and major interventions at weekly, monthly, and yearly frequencies respectively, yielding the best overall result with a 22% reduction in total delay. Among the evaluated strategies, this portfolio represents the most realistic approach for terminal operations, balancing routine preventive tasks with periodic deeper maintenance without excessive downtime. Light and frequent actions, such as 'Minor PM Weekly' strategy, provide efficient balance between planned downtime and reliability gain, achieving around a 14% delay reduction. In contrast, 'Major PM Weekly' performs worse than 'Major PM Yearly' because excessive PM adds substantial planned downtime without proportional reliability improvement, thereby reducing overall availability. Heavy but infrequent maintenance, such as 'Major PM Yearly', results in limited improvement, as failures tend to accumulate during long intervals between interventions.

7 Discussion

This chapter discusses the implications of the Bayesian Network (BN) analysis for system-level reliability and maintenance planning in container terminals. The results are interpreted in the context of the research questions, highlighting how the model captures delay propagation, subsystem behaviour, and the role of maintenance and operator factors. This section also includes the strengths and limitations of the model.

7.1. Interpreting the results

This subsection interprets the main findings of the BN analysis in terms of system behaviour, maintenance effectiveness, and delay propagation across terminal subsystems.

System-level interactions and delay propagation The BN effectively demonstrates how disruptions spread through interconnected subsystems in the terminal. The availability, efficiency, and delay nodes interacted with probabilistic dependencies that reflect real operational connections. Quay cranes (QCs) mainly rely on the timely arrival of empty horizontal transport (HT) units. In turn, the HT system depends on the yard crane (YC) efficiency and storage availability to finish cycles.

When any of these nodes dropped in availability or efficiency, the chances of delays in connected subsystems increased. A slowdown in HT operations significantly increased total delay because it restricted both the quay and yard interfaces. YC-related congestion further strengthened this effect by delaying HT discharge cycles. These findings confirm that the BN successfully illustrates the cumulative nature of delays across interdependent processes, by showing how local disruptions lead to performance losses throughout the entire terminal.

Subsystem behaviour Each subsystem behaved as expected in terms of physical and operational performance. For the QCs, wind was the main cause of delays. Strong winds directly reduced the operability and efficiency of the quay cranes. This increased total delays, even when other subsystems worked well. YCs were most affected by storage capacity. As yard occupancy rose, reshuffling operations increase, leading to longer cycle times and extended delays in horizontal transport. HT served as the key link between the quay and the yard. When its availability decreased, both upstream and downstream processes were affected right away.

Overall, the BN results reflected real operations. The performance of QCs depended mainly on the weather, YCs on yard utilization, and HT on its availability and congestion, all contributing to total delays.

Maintenance–availability trade-offs The results of BN showed that the medium weekly maintenance strategy struck the best balance between availability and reliability among the tested portfolios. However, this outcome should be interpreted within the scope of the model, which represents maintenance through its frequency and type but does not account for the specific technical actions performed during each intervention. In reality, the effectiveness of maintenance relies heavily on what is actually done during these activities. Performing high-level maintenance too often, such as doing major packages monthly or medium packages weekly, would not necessarily lead to significant improvements in reliability. Many actions, like component replacements or full overhauls, do not need to happen as frequently and may cause unnecessary downtime or excessive maintenance costs.

Thus, while the model suggests that moderate maintenance frequencies work best, this reflects the balance between preventive and corrective downtime instead of the specific content of the maintenance tasks. In practice, mixed strategies that combine regular medium-level maintenance with less frequent major overhauls are usually more effective, as they better match actual maintenance needs.

Human Factor The human factor was represented in the BN through the operator availability node, which shows how staffing shortages or disruptions in labor affect terminal operations. The results indicated that operator availability had a localized but noticeable impact on total delay, especially during extreme situations like strikes or significant absenteeism. Under normal operating conditions, changes in staffing levels did not greatly affect delay probabilities.

However, the model only captures this factor in probabilistic terms and does not distinguish between skill levels, fatigue, or coordination efficiency. These elements can be crucial for performance in the real world. In practice, these qualitative aspects of human behaviour could either worsen or lessen the effects of operator availability seen in the model.

7.2. Practical relevance

This section discusses the practical relevance of the developed BN framework by comparing it with other system reliability approaches and outlining its potential applications in terminal management.

Comparison with other system reliability modelling approaches Reliability Block Diagrams (RBDs) are effective for quantifying overall reliability in systems with independent and binary components and can clearly show how redundancy improves performance. However, they focus primarily on component-level reliability, describing whether individual elements succeed or fail within the system's overall structure. Therefore, an RBD cannot capture the conditional dependencies that dominate terminal operations. In this study's context, subsystem performances are interlinked, so assuming component independence would oversimplify the system's behaviour.

Fault Tree Analysis (FTA), in contrast, is useful for identifying causal relationships leading to a top event such as total delay. It provides a clear logical breakdown of contributing failures and remains an essential foundation for many reliability frameworks. However, once probabilities are assigned, an FTA is static; it cannot represent varying operational states, update when new information becomes available, or model feedback effects between subsystems.

The BN framework developed in this study builds on the FTA structure. It allows subsystem interactions, environmental influences, and human factors to be modelled within a single framework. Through its conditional dependencies, the BN captures how disruptions propagate across the quay, yard, and transport systems, while maintaining the flexibility to update probabilities when new data or evidence are introduced. This makes the BN particularly well suited for representing the uncertainty and interdependence inherent to container terminal operations.

Application in terminal management The developed BN framework can help terminal managers identify which operational factors most strongly influence total delay and overall reliability. Scenario and sensitivity analyses make it possible to test different conditions and enable decision-makers to quickly assess their combined effects on performance. Compared to conducting detailed simulation studies, the BN can provide quicker results and is easier to interpret, which makes it suitable for scenario testing or early decision-making.

In practice, the model can be used to study how different maintenance intervals affect downtime across subsystems, or to see how operator availability influences total delay. Factors such as weather and terminal busyness cannot be controlled, but including them in the model makes the analysis more realistic and helps explain performance variations under different conditions. This shows how operational choices, such as maintenance and staffing planning, interact with external factors to influence reliability and delay, supporting more informed operational decisions.

7.3. Strengths

The developed framework demonstrates several key strengths that contribute to its robustness and applicability. They reflect the model's design, implementation, and flexibility across diverse operational environments.

Modularity A key strength of the reliability framework is its modular structure. Each subsystem acts as an independent module within the BN, with its own set of variables and conditional relationships. With this structure, the performance and reliability of individual components can be analysed separately and then combined into a single system-level representation. Modularity also allows for updates or extensions without needing a complete rebuild. New components, dependencies, or influencing factors can be added as additional nodes or upgrading the already existing nodes with minimal changes to the existing structure.

Flexibility Due to this flexibility, the framework can be easily adjusted to different system configurations, operational scenarios, or levels of detail. For instance, if more detailed data on a specific subsystem becomes available, that module can be refined independently while maintaining consistency across the network. On the other hand, modules can be simplified when information is limited, ensuring the framework remains useful even in data-scarce situations.

Scalability The model is scalable as it can be applied across terminals of different sizes, operational capacities, and technological maturity. This scalability ensures that the same modelling principles can be applied, regardless of the system size.

7.4. Limitations

Despite its strengths, the proposed framework has several limitations that should be addressed in future research. These mainly concern data availability, model assumptions, and the simplified representation of dynamic system behaviour.

Data realism and expert-based assumptions The BN relies on assumed conditional probabilities for factors such as delay propagation, maintenance effects, and operator availability. These values were defined based on engineering judgement and conceptual understanding of terminal operations, rather than derived or fitted from empirical data. As a result, the model provides a qualitative representation of system behaviour rather than statistically validated performance estimates.

In modelling delay propagation, several simplifying assumptions were made to ensure the process was manageable while keeping the results easy to understand. It was assumed that one delay's impact on another follows a proportional and consistent pattern. This means that a delay in one subsystem, like QC operations, raises the chances of delays in related processes, such as HT or YC operations, in a steady way. However, feedback loops and queuing dynamics were not explicitly modelled. External factors, including weather, maintenance, and operators, were treated as separate contributors affecting subsystem performance instead of changing variables over time. These assumptions allow the framework to capture the main ways delay propagation occurs within the BN while keeping the model easy to compute. However, they also restrict its ability to show complex time-related dependencies or feedback effects that go in multiple directions.

For determining the scale and shape parameters, literature values were used. However, there was variability within the literature. While the Mean Time Between Failures (MTBF) and Mean Time to Repair (MTTR) are mentioned in the literature, it does not specify the size of the failure, leading into different Weibull parameters. For maintenance modelling, this uncertainty also affects how the shape and scale parameters are adjusted. For example, MTBF improvements and downtime penalties were modelled using fixed scaling constants (E_{ETA}, A_{ETA}, and PM duration) instead of data-fitted distributions. Consequently, the model shows plausible relative trends but not absolute performance levels.

Sampling and computational constraints Another limitation concerns the sampling process used for forward inference and sensitivity analysis. Although a large number of Monte Carlo samples were generated to ensure the stability of posterior probabilities, the results still depend on the chosen sample size and random seed. The sample size was selected based on judgment and preliminary testing rather than formal optimisation. Rare combinations of input conditions may not be fully captured in the sampling process, which can lead to minor inaccuracies in very low-probability outcomes such as severe delay scenarios.

Simplified maintenance modelling The model assumes all the equipment has the same maintenance policy. This assumption of uniform policy effectiveness across equipment (QC, HT, YC) overlooks manufacturer-specific or age-related differences. In reality, the frequency of the equipment being used is also taken into account for maintenance. In this model, the equipment is assumed to be in use with no stops, which can be a strong assumption for non-busy terminals.

While the maintenance sub-model introduces imperfect PM through parameter scaling, this formulation remains highly idealized. It treats maintenance actions as deterministic modifiers of the Weibull parameters rather than stochastic events with uncertainty. In reality, terminals often show varied maintenance effectiveness depending on part availability, technician skill, or wear state—all of which are missing from the current model.

Another important point to mention is that the preventive maintenance frequencies are modeled categorically (weekly, monthly, yearly) without considering opportunistic scheduling between equipment. Opportunistic maintenance, where preventive maintenance takes place when the system is not active, can make a huge impact on the equipment availability.

So as a result of these limitations, the model effectively captures theoretical trade-offs (How more PM leads into longer MTBF, and lower availability if overused) but underrepresents the logistical complexity of maintenance in real terminals.

Discretization and binning assumptions The BN variables were discretized into three qualitative states—Low, Medium, and High—to simplify interpretation and reduce model complexity. This three-bin structure was an assumed setting rather than derived from data. In practice, the number and placement of bins can be determined more objectively using clustering techniques, which identify natural groupings in continuous data (H. Liu et al., 2002). Applying such a data-driven approach could refine the model's sensitivity and improve how gradual changes are represented once sufficient empirical data become available.

Static BN structure – lack of temporal dynamics The current BN is static. It shows average states of reliability and delay, but it does not reflect changes over time. This limits its ability to capture ongoing degradation, realistic maintenance planning, or track cascading failures in real time.

Operator and human factors simplification Operator availability is represented through a small set of clear states, such as Shift and Strike. This assumes that all operators have the same skills and that there are no effects from the learning curve or fatigue. This simplification was necessary for analysis, but it oversimplifies human differences, especially in smaller terminals where staffing and shift changes lead to significant reliability variations. Additionally, the BN currently treats human and technical reliability as separate. In reality, operator errors and equipment wear and tear are connected. For example, a mistake in operation can increase the chances of failure.

The current model does not explicitly represent automated terminal operations. However, automation can be approximated by disabling or simplifying the operator-related nodes, effectively assuming continuous availability. Future extensions could include dedicated automation nodes to compare human-operated and automated scenarios more systematically.

Structural and scope limitations The analysis focuses exclusively on the vessel□emptying process rather than the full vessel turnaround cycle. This restriction simplifies the modelling of container flow and subsystem interactions while keeping the process direction consistent from quay to yard. As a result, vessel loading and combined loading–discharging operations are not represented, which limits the model's ability to capture two-way interactions or overall turnaround performance.

The BN structure looks at the interactions between the quay, transport, and yard, leaving out gate, rail, and hinterland operations. This focus isolates the main interdependent subsystems but overlooks the potential spread of delays upstream and downstream.

In the model, weather only has an impact on the QC and is not included for the HT and YC subsystems. Additionally, environmental factors like wind, rain, and visibility are modeled separately. The relationships between them—such as how strong winds often come with reduced visibility—were not included. This separate treatment simplifies the CPTs, but it makes the model less realistic in terms of extreme weather situations.

8 Conclusion

This study developed a system-level reliability modelling framework that illustrates how failures, maintenance activities, and operational disruptions propagate across interconnected subsystems in container terminal operations. The aim was to combine reliability analysis with probabilistic reasoning to give a better understanding of how technical and operational factors together affect delay behavior and system performance.

The research showed that system reliability in dynamic operational environments can be effectively assessed using a Bayesian Network (BN) framework. The BN captures probabilistic dependencies between equipment reliability, maintenance effectiveness, operator availability, and environmental conditions, linking these factors to overall system performance. Through Conditional Probability Tables (CPTs), the model quantifies how local failures, maintenance decisions, and external disturbances propagate through the system to affect reliability, availability, and delay. Scenario and sensitivity analyses identify the factors that most strongly influence these outcomes.

To explore the broader research aim in more depth, the study was guided by two sub-questions that focus on different but related aspects of the proposed framework. The first looks at how to model reliability at the system level, going beyond individual component failures. The second looks at how the framework can be used to analyze the effects of maintenance, operational, and environmental factors on performance.

Sub-question 1: How can reliability be modelled beyond component failures to capture system-wide dependencies and operational disruptions?

The research expanded traditional reliability modeling by capturing interdependencies and cascading effects between terminal subsystems. Using Fault Tree Analysis (FTA) as a structural foundation, the BN was developed to include both technical and operational factors. The initial base model represented the key operational and environmental interactions within the terminal, with nodes for equipment failure, subsystem availability, efficiency, and delay propagation. The top node, total delay, reflected the combined system-level outcome resulting from these interactions. To represent subsystem efficiency, the model included environmental nodes such as weather conditions affecting quay crane performance, yard storage fullness representing yard crane congestion, and terminal busyness influencing horizontal-transport operations. This structure explicitly links reliability parameters to time-based performance effects. It shows how reliability loss appears as increased delays at the system level.

The complete model extended this framework by incorporating maintenance and operator performance as additional influencing factors, providing a more realistic representation of system-level reliability and delay behavior. These nodes directly affected equipment availability by capturing the impact of operator efficiency and equipment health on performance. Preventive maintenance (PM) was modelled by modifying the probabilities of equipment failure and recovery. Maintenance effectiveness was represented through Weibull based reliability parameters, where the scale (η) and shape (β) parameters were adjusted using maintenance effect multipliers to account for imperfect repair conditions. This adjustment allowed the model to capture how preventive actions extend the mean time between failures and reduce degradation rates over time, enhancing the network's ability to reflect real-world maintenance behavior.

Sub-question 2: How can system-level analysis be used to evaluate the impact of maintenance, operator availability, terminal situation, and environmental factors on overall reliability and performance?

The analysis phase looked at how maintenance, operator availability, terminal situation and environmental factors affect behavior at the system level. The BN allowed for a thorough examination through forward inference and sensitivity analysis. Forward inference was used to calculate the likelihood of delay outcomes under specific operational and environmental conditions. It was used to analyze the effects of different maintenance frequencies, operator efficiency, and external disruptions like weather or congestion. Sensitivity analysis measured the impact of each variable on key performance indicators, especially total delay and subsystem availability, by observing how changes in input probabilities differed from a defined baseline.

The results showed that the BN effectively represented how disruptions in one part of the system spread through interconnected subsystems. This leads to cumulative effects on overall reliability and delay. The analysis also confirmed that the model's predictions matched operational expectations. This demonstrates its ability to capture realistic terminal behavior under different conditions. In practice, this offers a structured method to test operational strategies and assess the effects of maintenance or staffing changes before they happen. This approach supports better and more proactive reliability management in terminal operations. It also demonstrates that the BN can serve as an efficient pre-simulation layer, identifying the most critical scenarios and parameters to explore in more detailed discrete-event or agent-based simulations.

Overall Contributions The proposed BN framework bridges the gap between traditional reliability engineering and operational performance modeling by integrating technical, human, and environmental factors within a single structure. Unlike previous BN applications that focused mainly on safety or resilience assessment, this framework explicitly links reliability states to operational delay behavior, quantifying how failures and maintenance decisions influence system performance. It provides a decision support tool that helps analyze how local failures and operational disturbances propagate through interconnected subsystems and influence overall delay behavior. Compared to simulation-based approaches, the BN allows much quicker exploration of scenarios and system behavior. It provides probabilistic insights without the long runtimes of detailed simulations, making it practical for early-stage planning and decision support.

The study addresses the limitations identified in existing approaches, which often model reliability and operational performance separately or rely on component-level assumptions. The developed framework unifies these domains by representing dependencies between maintenance, operator availability, and environmental conditions as probabilistic relationships. Although it was created for container terminals, the framework can be applied to other complex systems with limited data, where reliability loss and operational performance are closely related.

Future Work Future research could build on the developed framework by adding temporal dynamics through a Dynamic Bayesian Network (DBN). This would allow the model to capture how reliability, degradation, and maintenance effects evolve over time rather than being represented as static relationships. In parallel, Bayesian updating techniques could be implemented to continuously revise probability distributions as new operational data become available, enabling the model to learn and adapt over time. Such an extension would lay the foundation for predictive maintenance, where the model anticipates equipment failures based on observed degradation patterns and schedules interventions before breakdowns occur. Cost-based optimization can also be included for evaluation of maintenance policies, enabling a balance between reliability improvement and financial aspects. Including operator skill level as a probabilistic factor would enhance the model's representation of human performance. This would provide a better understanding of how workforce expertise affect the delay behavior. Furthermore, incorporating operational data for empirical validation would allow for more precise calibration of the model. This would reduce reliance on expert estimates and improve the accuracy and generalization across different operational conditions.

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Scientific Paper

System Level Reliability Modelling and Analysis of a Container Terminal

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Abstract:
This paper presents a system-level reliability modelling framework for container terminals that integrates failure behaviour, maintenance, and delay propagation across interconnected subsystems. System reliability modelling approaches such as Fault Tree Analysis (FTA) and Reliability Block Diagrams (RBD) describe how component failures contribute to system failure but cannot capture interdependent component behaviour, while simulation-based approaches demand extensive data and computation. To address this gap, a Bayesian Network (BN) framework is developed to represent probabilistic interactions between equipment reliability, maintenance effectiveness, operator availability, and environmental variability. The model is applied to quay crane (QC), yard crane (YC), and horizontal transport (HT) subsystems using Weibull-based reliability parameters and imperfect maintenance formulations. Numerical analyses show that moderate preventive maintenance schedules substantially improve availability and reduce total delay, while excessive maintenance yields diminishing returns. Horizontal transport acts as the key coupling path for delay propagation. The approach is modular and applicable to other terminal configurations or comparable complex systems, supporting maintenance planning and scenario analysis.

Keywords: Bayesian Networks, System-level reliability, Container terminal, Delay propagation, Preventive maintenance

1. INTRODUCTION

Reliability is essential for maintaining the safety and efficiency of complex industrial systems. It reflects a system's capacity to perform as intended under defined condition and directly influences operational stability, cost efficiency, and service quality [Rausand and Høyland, 2004].

System reliability modelling approaches such as Reliability Block Diagrams (RBD) and Fault Tree Analysis (FTA) provide structured ways to assess failure logic and overall reliability. However, they are not suited for analysing dynamic, interdependent behaviour in complex operations. They typically assume static system states and do not reflect how degradation, maintenance, and operational disruptions evolve or interact over time. In reality, complex industrial systems function as tightly coupled networks where technical components, human actions, and external conditions continuously interact. Failures or inefficiencies in one part can propagate through shared processes, creating bottlenecks, cumulative delays, and performance losses.

Probabilistic and simulation-based approaches have been developed to address these limitations. Bayesian Networks (BNs) combine probabilistic reasoning with a graphical representation that captures causal relationships and uncertainty [Langseth and Portinale, 2007]. Simulation models, such as discrete-event and agent-based approaches, can reproduce detailed process interactions and delay propagation [Carlo et al., 2014, Dragović et al., 2017, Park et al., 2024], yet they require extensive data and computation, making them less practical for rapid scenario evaluation or early-stage decision support.

This paper presents a system-level reliability framework that integrates technical, human, and environmental factors to analyse how disruptions propagate through interconnected subsystems. The framework is designed to be modular and applicable to other complex systems characterized by interacting reliability, maintenance, and operational factors. A container terminal is used as a case study to demonstrate the approach, as it provides a realistic setting with strong subsystem dependencies between quay cranes (QC), horizontal transport (HT), and yard cranes (YC).

The research is guided by the following questions:

- **RQ1:** How can reliability be modelled beyond component failures to capture system-wide dependencies and operational disruptions?
- **RQ2:** How can system-level analysis be used to evaluate the effects of maintenance, operator availability, and environmental factors on overall reliability and performance?

2. RELATED WORKS

System reliability analysis has traditionally relied on deterministic methods such as FTA and RBD to assess component-level reliability and identify critical failure paths [Friederich and Lazarova-Molnar, 2024, Rausand and Høyland, 2004]. While these techniques remain foundational, they primarily capture static relationships and are limited in addressing uncertainty propagation across subsystems. BNs extend these approaches by combining probabilistic reasoning with a graphical representation, allowing for inference under uncertainty and integration of both data and expert judgment [Langseth and Portinale, 2007].

Delay propagation has been widely studied in other transportation domains such as aviation and rail networks [Liu and Ma, 2008, Ulak et al., 2020], where BNs have been used to trace how disruptions evolve through interconnected subsystems. However, comparable research in container terminals remains limited. Most performance analyses rely on simulation-based approaches to study congestion, resource allocation, and vessel scheduling. Discrete-event simulation (DES) and agent-based modeling (ABM) dominate terminal performance research due to their ability to capture detailed operational dynamics and process interactions [Carlo et al., 2014, Dragović et al., 2017, Yang et al., 2004, Park et al., 2024]. While these methods provide high realism, they require long computation times and detailed data that are often unavailable in early analysis stages. Consequently, simulation models are less suited for rapid reliability assessments or probabilistic reasoning under uncertainty.

In the maritime and port context, BNs have been applied primarily to assess operational safety, risk, and resilience rather than performance and delay propagation. Alyami et al. [2019] developed a fuzzy-rule-based BN for port risk analysis, while Hossain et al. [2019] used a BN framework to evaluate port resilience and recovery performance. Similarly, Wang et al. [2023] applied a BN model to study port robustness and flexibility. These studies highlight the versatility of BNs in modelling uncertainty and complex interactions but generally focus on safety and resilience metrics rather than operational reliability.

This study contributes to the literature by proposing an integrated probabilistic framework that links reliability behaviour, maintenance strategies, and delay propagation within a single BN structure. The framework is modular and flexible, enabling system-level reliability analysis across different container terminal configurations as well as other complex operational systems where technical, human, and environmental factors interact.

3. MODEL DESCRIPTION

3.1 Methodology

The proposed framework integrates FTA with BN to evaluate system-level reliability and delay propagation in complex operational environments. FTA decomposes the top event—total operational delay—into its contributing causes and intermediate failure mechanisms. These logical relationships are then translated into probabilistic dependencies within the BN, allowing for quantitative reasoning under uncertainty. Forward inference and sensitivity analysis are applied to evaluate system performance under varying maintenance, environmental, and operational conditions.

3.2 System Description

The methodology was implemented for a container terminal, which serves as the transfer point between maritime and inland transport, where containers are moved between vessels, storage yards, and external trucks or trains. Terminal operations are organized into several interconnected stages that must function in coordination to maintain efficient cargo flow.

The process starts with handling vessels at the quay, where quay cranes (QC) lift containers on and off ships. After unloading, horizontal transport (HT) vehicles, such as terminal tractors (TTs) or automated guided vehicles (AGVs), transfer containers to the storage yard. In the yard, yard cranes (YC), typically rubber-tyred or rail-mounted gantry cranes, stack, retrieve, and rearrange containers. This system creates a closed operational loop where the quay, transport, and yard subsystems rely on each other. Disruptions in any part can delay the entire process and impact vessel turnaround time.

To represent these dynamics, the developed framework models three main subsystems: QC, HT, and YC. Each one is modelled based on its reliability, availability, and efficiency, showing how technical performance and environmental conditions affect overall system output. Gate operations and external logistics processes are not included in the analysis since they mainly serve as boundaries and do not directly influence the internal coordination between quay and yard operations. The analysis focuses on the vessel-emptying phase of operations. Figure 1 illustrates the container terminal layout, with the red box indicating the modelled scope.

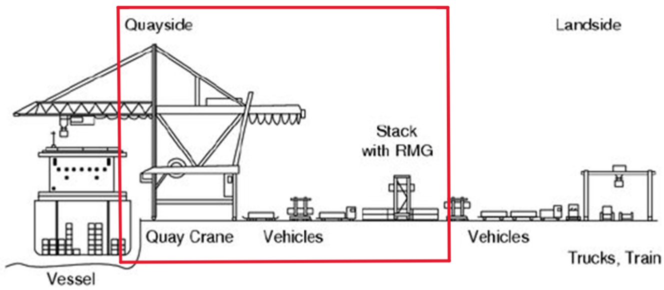

Fig. 1. Container terminal system overview (adapted from Voss et al. [2004])

3.3 Node Categories

Each subsystem (QC, HT, YC) contains nodes representing equipment health, availability, efficiency, and operator status, which together determine delay outcomes. In the base model, the BN includes only technical and environmental dependencies, while the complete model extends this structure by incorporating preventive maintenance and operator availability nodes. Figure 2 illustrates the overall BN structure.

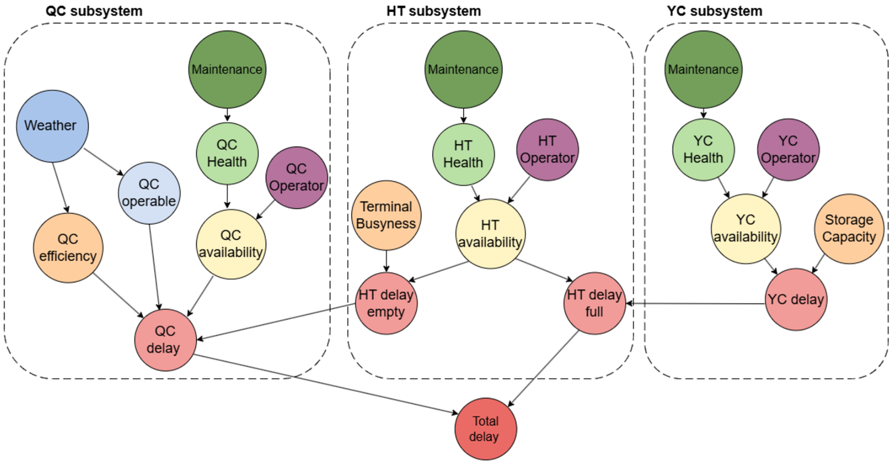

Fig. 2. Simplified BN structure showing QC, HT, and YC interconnections

The BN consists of the following node categories:

- **Equipment Health:** Represents the probability of technical failure for QCs, HTs, and YCs, modelled using a Weibull distribution. It connects directly to availability nodes, linking mechanical condition to system operability.
- **Availability:** Expresses the expected fraction of operational time for each subsystem, discretised into low, medium, and high states.
- **Efficiency:** Captures subsystem performance under environmental and congestion-related constraints. QC efficiency is affected by wind, rain, and visibility; HT efficiency depends on terminal busyness; and YC efficiency is influenced by yard storage utilisation.
- **Operator Availability:** Represents the presence of qualified personnel for each subsystem, distinguishing between day/night shifts and strike conditions. Availability is set to zero during strikes and slightly reduced at night.
- **Delay Nodes:** Defines performance outcomes at both subsystem and terminal levels (low, medium, high). Each subsystem's delay depends on its availability, efficiency, and interdependencies with other nodes, while the total delay node aggregates their combined effects on terminal performance.

3.4 Equipment Health Modelling (Base Model)

In the base BN, equipment health is modelled using a Weibull distribution representing the probability of failure over time. The distribution is characterized by the scale parameter η (characteristic life) and the shape parameter β (failure-rate trend). The mean time between failures (MTBF) is derived as:

$$\mathrm{MTBF} = \eta\,\Gamma\left(1+\frac{1}{\beta}\right),$$

where $\Gamma(\cdot)$ denotes the Gamma function.

Only corrective maintenance is considered in the base model. When a failure occurs, the equipment is repaired and restored to full operation, starting a new reliability cycle without accumulated degradation. To reflect the effect of equipment ageing, different η and β values are assigned to new, mid-life, and old equipment categories, based on literature-informed assumptions about degradation in container-handling equipment. Higher η and lower β represent newer, more reliable equipment, whereas lower η and higher β indicate accelerated wear in older assets.

Equipment availability (A) is calculated from the relationship between MTBF and the mean time to repair (MTTR) as:

$$A = \frac{\mathrm{MTBF}}{\mathrm{MTBF}+\mathrm{MTTR}}$$

This expression provides the proportion of time that equipment remains operational, combining the effects of both reliability and repair duration.

3.5 Maintenance Modelling (Complete Model)

In the complete BN, preventive maintenance (PM) is incorporated into the model. Three PM levels are considered—*minor*, *medium*, and *major*—corresponding to increasing intervention scope and downtime. Each level is assigned a frequency policy (*None*, *Weekly*, *Monthly*, or *Yearly*), which determines the expected number of interventions per year n_t for type $t \in \{\text{minor, medium, major}\}$. Event durations are equipment-specific (e.g., QC: 2/6/24 h; YC: 3/6/20 h; HT: 1/2/4 h for minor/medium/major), yielding a total planned PM time:

$$T_{\mathrm{PM,year}} = n_{\mathrm{minor}}\,t_{\mathrm{minor}} + n_{\mathrm{medium}}\,t_{\mathrm{medium}} + n_{\mathrm{major}}\,t_{\mathrm{major}}$$

Per-event improvement multipliers (e_η, e_β) capture the average rejuvenation effect on the Weibull scale and shape parameters (e.g., minor: e_η=0.10, e_β=0.05; medium: 0.25, 0.15; major: 0.60, 0.30). To combine multiple PM types and frequencies without overestimating gains, the cumulative annual effectiveness is calculated as:

$$E_\eta = 1 - \prod_{t\in\{\text{minor, medium, major}\}} (1-e_{\eta,t})^{n_t/F_N}, \qquad (1)$$

$$E_\beta = 1 - \prod_{t\in\{\text{minor, medium, major}\}} (1-e_{\beta,t})^{n_t/F_N}, \qquad (2)$$

where the frequency normalization factor F_N=12 limits asymptotic growth.

PM effects are applied through a virtual-age formulation based on Kijima's Type I model, representing an imperfect repair process in which maintenance partially restores but does not fully renew equipment condition (Kijima [1989]). Per-event restoration fraction is expressed with ρ_t (e.g., $\rho_{\min}$=0.10, ρ_{med}=0.30, ρ_{maj}=0.60). The retained-age fraction over one year is given by:

$$\phi = (1-\rho_{\min})^{n_{\min}/F_N}(1-\rho_{\text{med}})^{n_{\text{med}}/F_N}(1-\rho_{\text{maj}})^{n_{\text{maj}}/F_N}$$

The updated Weibull parameters are then calculated as:

$$\eta' = \frac{\eta_0}{\phi}, \qquad \beta' = \beta_0 \left[1 - \min(B_\beta E_\beta, \text{max drop})\right],$$

where B_β is a sensitivity coefficient and *max drop* limits the reduction in β (e.g., 0.30).

Given T yearly operating hours, the expected number of failures per year f (under minimal repair between PM events) satisfies:

$$f = \left(\frac{T - T_{\text{PM,year}} - f \cdot \text{MTTR}}{\eta'}\right)^{\beta'}, \tag{3}$$

which is solved iteratively. The resulting operational availability is expressed as:

$$A = 1 - \frac{T_{\text{PM,year}}}{T} - \frac{f \cdot \text{MTTR}}{T}.$$

PM policies affect the *Equipment Health* node by updating $(\eta, \beta) \rightarrow (\eta', \beta')$, and influence the *Availability* node through $T_{\text{PM,year}}$ and f, thereby propagating their effects to subsystem and total delay nodes in the BN.

4. NUMERICAL RESULTS

The Bayesian Network model was implemented in Julia using the BayesNets.jl package. Forward inference was applied to compute posterior delay probabilities under different subsystem and maintenance states, while sensitivity analysis quantified the relative influence of each node on total delay.

4.1 Base Model

The base BN captures the core subsystem dependencies (QC, HT, YC), environmental effects (wind, rain, visibility), and terminal situations such as terminal and storage busyness. Maintenance and operator factors are excluded to establish a neutral reference scenario.

Delay Propagation. Delay propagation was examined to quantify how local disruptions spread through interconnected subsystems. The BN structure explicitly captures these causal links: QC delay depends on HT availability, while HT delay is influenced by YC performance through container handover constraints. By conditioning the network on specific delay states—such as setting HT delay (Loaded) or YC delay to a high level—the resulting posterior probabilities reveal how congestion or equipment failures in one area propagate across the terminal.

The analysis shows that high delays in HT (Loaded) produce the strongest cascading effects, increasing the probability of severe total delay by more than 150% relative to baseline conditions. YC delays also propagate upward, raising HT delays by approximately 80% and total delay by 130%. In contrast, QC delays, though critical for vessel operations, have a more localized impact, as their influence mainly effects the quay-side interface. These

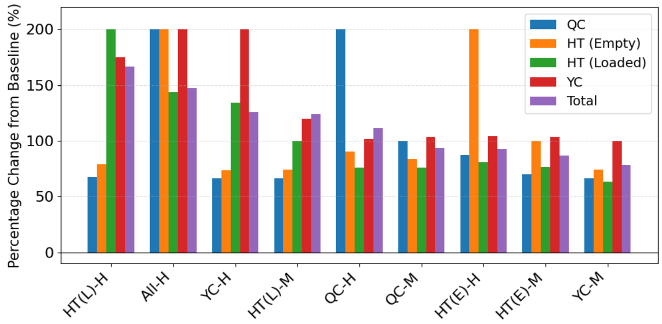

Fig. 3. Delay propagation between subsystems

results highlight the central role of horizontal transport as the main coupling mechanism between quay and yard operations.

Equipment Ageing. The influence of equipment age on reliability and availability was evaluated using age-dependent Weibull parameters for new, mid-life, and old equipment categories. As shown in Figure 4, availability decreases gradually with age across all subsystems, reflecting the cumulative effects of wear, fatigue, and more frequent corrective repairs.

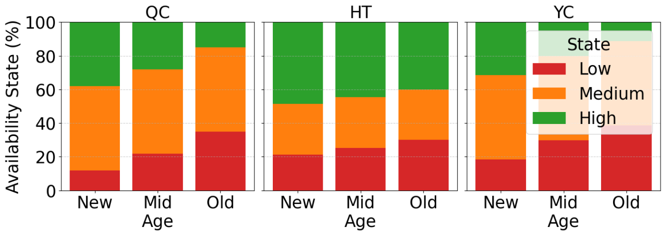

Fig. 4. Availability state distribution for new, mid-life, and old equipment

QC availability declines from approximately 97% for new units to 95% for older ones, while YC availability drops from 94% to 91%. HT follows a similar but slightly less pronounced trend.

As subsystem availability decreases, the likelihood of severe delay states increases, emphasizing the importance of timely maintenance and replacement planning to sustain operational reliability. The effect of availability on overall delay performance is shown in Figure 5.

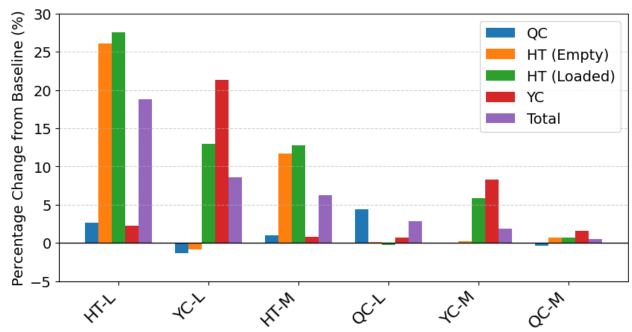

Fig. 5. Equipment availability sensitivity

When HT availability decreases from high to low, the probability of severe total delay increases by more than 18%, reflecting its central role in maintaining continuous container flow. YC availability also has a noticeable impact: low YC availability increases YC delay by about 22% and indirectly raises total delay by nearly 8%. In contrast, QC availability has a smaller system-wide effect, since disruptions are partially absorbed by the buffering capacity of the horizontal transport subsystem.

4.2 Complete Model

The complete model extends the base BN by including operator availability and preventive maintenance effects, representing the two main controllable factors in terminal operations. This enhanced version captures how human performance variability and maintenance schedules affect subsystem reliability, downtime, and total delay propagation.

Operator Impact. Operator-related effects were analyzed to assess how variations in staffing and labour disruptions influence subsystem and total delays. Two scenarios were modelled: normal shift operations (day and night) and strike conditions that represent complete operator unavailability. Table 1 summarises the relative change in delay probabilities compared with the baseline day-shift scenario.

Table 1. Scenario-based delay comparison relative to baseline.

Scenario	QC (%)	YC (%)	HT (%)	Total (%)
Strike	+111.8	+110.2	+159.4	+108.3
Night	+6.3	+0.2	-0.2	+1.8
Baseline	+0.0	+0.0	+0.0	+0.0

The results show that strike conditions have a severe impact across all subsystems, with total delay more than doubling relative to baseline. QC operations are most affected due to their reliance on certified operators. In contrast, the night shift scenario produces only minor deviations, with total delay increasing by less than 2%, reflecting slightly reduced staffing efficiency and coordination speed. These findings indicate that while normal shift variation has a limited influence on system performance, labor disruptions such as strikes can severely constrain terminal operations.

Maintenance Portfolios. The effect of different preventive maintenance (PM) strategies was evaluated through a portfolio-based analysis combining maintenance level (minor, medium, major) and frequency (weekly, monthly, yearly). Figure 7 illustrates the results for QC, the most reliability-critical subsystem. The figure compares the share of planned and unplanned downtime for each PM policy, showing how preventive interventions shift total downtime composition.

The baseline scenario without preventive maintenance (No PM) yields an availability of about 82%, with approximately 18% of total operational time lost to corrective repair. Introducing medium-level weekly PM increases availability to 95%, reducing unplanned downtime by more than 1,100 hours per year. Moderate portfolios such as *Minor Weekly + Medium Monthly* achieve nearly the same improvement (around 94%) with far less planned maintenance effort, representing the most efficient balance between maintenance workload and reliability gain. In contrast, heavy portfolios such as *Major Weekly* produce diminishing returns; although failures nearly disappear, excessive planned downtime reduces overall availability to below 86%.

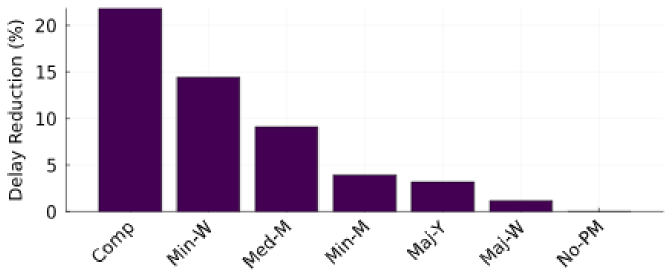

Fig. 6. PM Strategy Percentage Improvement

These improvements in equipment availability translate directly into operational performance, as shown in Figure 6. Comprehensive (Minor weekly + Medium monthly + Major yearly) and moderately frequent PM strategies produce the largest reductions in total delay, with diminishing returns beyond a certain intervention level. The figure demonstrates that moderate PM portfolios not only minimise unplanned downtime but also yield the most significant delay reduction relative to maintenance effort. This highlights how reliability improvements achieved through preventive maintenance propagate through interconnected subsystems, ultimately influencing delay performance at the terminal level.

Similar trends were observed for HTs and YCs. For HT, the short repair time and built-in redundancy make light, frequent maintenance most effective, while YC performance responds best to medium-frequency policies. These consistent patterns confirm that moderate, regular PM offers the highest efficiency in maintaining system reliability without excessive downtime.

5. DISCUSSION

The proposed BN framework is modular and flexible, allowing new components or dependencies to be added without altering the overall structure. It is suitable for terminals of different sizes, degrees of automation, and operational settings, and can be extended to other complex systems beyond port operations. Unlike traditional methods such as FTA or RBD, the BN approach can represent probabilistic dependencies and uncertainty propagation between subsystems, offering a more integrated view of system reliability and performance. The framework can be used for rapid scenario exploration and reliability assessment without the heavy data and runtime demands of full simulation models.

Despite these advantages, the model remains constrained by the number of simplifying assumptions required for its implementation. Several input parameters, such as maintenance effectiveness and operational dependencies, were derived based on expert judgment rather than from consistent field measurements. Subsystem relationships were treated as static instead of changing over time. These simplifications lower quantitative accuracy and restrict the model's capability to capture feedback effects.

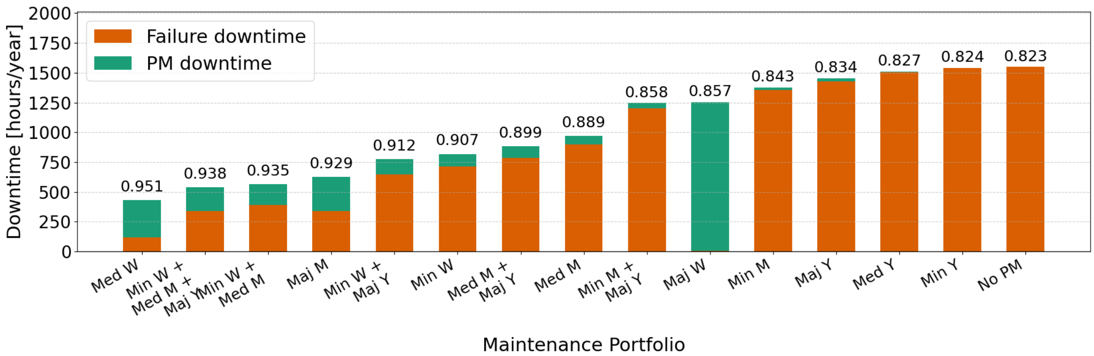

Fig. 7. QC downtime distribution under different preventive maintenance policies

Future efforts should focus on integrating empirical data and dynamic models to enhance accuracy and support predictive reliability analysis in actual operational settings. A Dynamic Bayesian Network (DBN) can be used to capture how reliability, degradation, and maintenance effects evolve over time. Furthermore, integrating Bayesian updating could further strengthen the approach by allowing probability distributions to adapt as new operational or maintenance data become available, improving accuracy through continuous learning.

6. CONCLUSION

This work introduced a probabilistic framework for analyzing system-level reliability in container terminal operations. Building on Fault Tree Analysis (FTA) structure, the Bayesian Network (BN) approach captures how technical reliability, maintenance actions, and operational conditions interact within a single structure. Its modular design makes the framework flexible and transferable, allowing extensions to different terminal configurations and other complex, interdependent systems. Beyond providing quantitative reliability assessment, it offers a practical basis for decision support by linking engineering insight with probabilistic reasoning.

The results show that preventive maintenance plays a decisive role in improving equipment availability, although overly frequent interventions lead to diminishing returns due to excessive planned downtime. HT acted as the key coupling element between quay and yard systems, driving the propagation of operational delays. Operator-related disruptions, particularly strikes, had an immediate and severe effect, highlighting the vulnerability of labour-dependent processes.

Overall, the framework provides a foundation for linking reliability analysis with operational performance. By capturing the interactions between technical, human, and environmental factors, it offers a systematic way to interpret and predict how local disruptions translate into system-wide delays.

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B

Environmental Node Modelling

In order to determine the Conditional Probability Tables (CPTs) for weather nodes, daily weather data was obtained from Koninklijk Nederlands Meteorologisch Instituut (KNMI), 2025 open data archive, as an example data. The dataset contains daily weather measurements for station 344, located in the Rotterdam region, and includes data ranging from October 1956 to April 2025. During the analysis, only the last 5 years was included.

B.1. Wind

High and extreme wind conditions can cause increased container sway, reduced crane precision, and, in severe cases, temporary shutdowns for safety. The Beaufort level is a standardized scale used to describe wind strength based on observed effects or measured wind speed, ranging from 0 (calm) to 12 (hurricane force), widely used in maritime operations (National Weather Service, 2023). Table B.1 outlines the thresholds used to classify wind risk levels.

Beaufort Level	**Wind Speed (m/s)**
6 – Strong Breeze	10.8 – 13.8
7 – Near Gale	13.9 – 17.1
8 – Gale	17.2 – 20.7
9 – Strong Gale	20.8 – 24.4
$\geq$10 – Storm+	$>$ 24.5

Table B.1: Wind classification based on the Beaufort scale. Wind speeds are 10-minute means measured at 10 m height (adapted from van den Bos, 2015).

In general, international standards and port authorities assume that ports remain operational under wind conditions up to Beaufort scale levels 6 to 8 (van den Bos, 2015). At Beaufort 6 and 7, port-specific policies vary: some terminals may continue operations with caution, while others may choose to suspend crane activity depending on equipment type, wind direction, and safety margins. While crane drivers are generally able to correct for sway caused by head-on winds, skew—especially from diagonal winds—is more difficult to manage and may lead to operational inefficiencies. Crane operations are typically suspended from Beaufort 8 onward, as wind speeds at this level pose significant safety risks and can cause uncontrollable sway and skew of suspended containers (van den Bos, 2015).

According to data found online, over a 14-year period, 445 days had wind over 11.8 m/s (roughly Beaufort 6) and 27 days had winds over 17 m/s (roughly Beaufort 8). Table B.2 summarizes the estimated Quay Crane (QC) efficiency levels under increasing wind conditions, reflecting practical limits informed by terminal practice and safety standards.

Beaufort Level	Estimated QC Efficiency	Occurrence Probability
Beaufort 6–7	50%	8.7%
Beaufort 8 or higher	0%	0.3%

Table B.2: Estimated QC efficiency and occurrence probability under high wind conditions based on Beaufort classification

B.2. Rain

Daily precipitation data (in 0.1 mm increments) from the KNMI dataset was analyzed to classify each day according to rainfall intensity. Table B.3 defines the thresholds used to distinguish between rain categories such as Light, Moderate, and Heavy. Based on this classification, Table B.4 presents the probability of each rain category occurring on a given day during the observation period from 2020 to 2025.

Rain Category	Daily Precipitation (mm)
None	0 mm
Light	0.1 – 2.0 mm
Moderate	2.1 – 10.0 mm
Heavy	$>$ 10.0 mm

Table B.3: Classification criteria for daily rain categories based on KNMI precipitation data

Rain Category	Probability (%)
None	37.11
Light	33.66
Moderate	21.07
Heavy	8.16

Table B.4: Probability of daily rainfall categories based on KNMI station 344 (Rotterdam) data from 2020 to 2025.

This classification aims to capture the potential operational impact of rain on QC activities. Table B.5 presents the estimated QC efficiency ranges associated with each rain category.

Rain Category	Estimated QC Efficiency
None	100%
Light	98%
Moderate	85%
Heavy	70%

Table B.5: Estimated QC efficiency under different daily rain conditions based on observed precipitation

B.3. Visibility

For determining the visibility, the minimum (VVN) and maximum (VVX) daily visibility values, measured in tenths of kilometers, were used. Data was converted to kilometers. Days were classified into four fog categories: Clear, Light Fog, Normal Fog, and Dense Fog. Fog classification criteria based on daily minimum and maximum visibility can be found in Table B.6.

Fog Level	Classification Criteria
Clear	Minimum visibility $>$ 1.0 km
Light Fog	Minimum visibility $\leq$ 1.0 km and $>$ 0.5 km
Moderate Fog	Minimum visibility $\leq$ 0.5 km and $>$ 0.2 km
Dense Fog	Minimum visibility $\leq$ 0.2 km **and** maximum visibility $\leq$ 0.5 km

Table B.6: Fog classification criteria based on daily minimum and maximum visibility

The relative frequency of each category was computed to derive the fog level probabilities used in the BN model can be found in Table B.7.

Fog Level	Probability (%)
Clear	86.37
Light Fog	3.45
Moderate Fog	4.93
Dense Fog	5.25

Table B.7: Fog level probabilities based on daily visibility data from KNMI (station 344, 2020–2025).

Fog can impact QC efficiency due to visibility-related challenges such as reduced spreader alignment accuracy. Table B.8 summarizes the estimated efficiency levels associated with each fog category based on observed visibility data.

Fog Level	Estimated QC Efficiency
Clear	100%
Light Fog	98%
Normal Fog	90%
Dense Fog	70%

Table B.8: Estimated QC efficiency under different fog conditions, based on daily minimum and maximum visibility data