A Modelling Approach to Railway Bridge Asset Management

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Abstract

In today's modern world, society are accustomed to disposable products, temporary services and frequent replacements. The art of maintaining and renewing assets has been somewhat lost. However, in the pursuit of financial performance, comes the need to effectively manage assets. Management of a large portfolio of infrastructure assets is a complex and demanding task for infrastructure owners. Not only is the coordination of a large organisation difficult to align, but every decision is scrutinised by regulatory bodies. For infrastructure portfolio managers, decision support tools are becoming increasingly more useful. This is particularly relevant to railway structures as a result of their diversity and age.

A thorough literature review (Chapter 2) is carried out to understand what decision support tools, known as Bridge Management Systems (BMSs), are currently available for railway bridge portfolio managers. The modelling approaches which have been used as the foundation of the BMSs are analysed (Chapter 3). Of these, the most appropriate modelling technique is selected for development of a new approach for a decision support tool. The tool comprises of a number of different modules, each with its own characteristics, data sources and features (Chapter 4). The model is presented, as well as detailed descriptions of each of the modules and how they work.

During the literature review stage, a number of studies mentioned that there are external factors that affect deterioration. However, very few studies were able to pinpoint what these factors were, how much they affected deterioration and what the operational, financial and management impacts were. To that effect, a number of different factors were analysed (Chapter 5) to ascertain if they have an effect on bridge deterioration. The key factors were identified and their deterioration profiles incorporated into a probabilistic Petri-Net (PN) model, calibrated with

historical data. From these, comparative model outputs pinpointing which factors affect bridge deterioration the most can be computed. Finally, simulations were carried out on the PN model to evaluate which of the factors would have the most financial effect for a transport agency. This allows bridge managers to categorize bridges in different deterioration groups allowing the definition of different optimal inspection and maintenance strategies for each group.

Literature also revealed that there are a number of sources of variability in bridge asset management. A study was undertaken to ascertain, using expert judgement, what the main causes of variability are in the process (Chapter 6). These include variability in defect identification, imperfect repairs and variability in intervention costs. These factors were then incorporated into the existing PN model developed for Whole Life-Cycle Costing (WLCC) analysis of bridge assets. The resulting model is able to replicate some of the complex decisions made during bridge asset management. Inevitably, introducing variability into the model causes operational issues which, in turn, causes WLCC to increase, however this is a critical insight to be able to give bridge portfolio managers more robust outputs that more similarly replicate the real world.

This research has also identified that complex models often have a heavy computational burden. A study was carried out to accelerate simulations of PN models with General-Purpose Graphics Processing Units (GPGPUs) (Chapter 7). GPGPUs are composed of many smaller, parallel compute units which has made them ideally suited to highly parallelized computing tasks. The efficiency of different approaches to parallelization of the problem is evaluated. The developed framework is then used on the railway bridge PN model. The results obtained show that this method allows the combination of complex PN modelling with rapid computation in a desktop computer.

A final piece of research was undertaken to perform optimisation with the railway bridge PN model (Chapter 8). This study utilised the foundation rail-

way bridge PN model, the Local Environmental Factors (LEFs), the variability factors and the GPGPU acceleration. A Hybrid Multi-Objective Genetic Algorithm (MOGA) approach is accelerated with GPGPUs to find the optimal inspection regime to minimise both the WLCC of railway bridges and the risk of being in a poor condition. The proposed Hybrid Genetic Algorithm (GA) approach is able to accelerate the process by over 30 times compared to the traditional GA approach. The results obtained demonstrate a potential 9% reduction in overall WLCC for UK railway bridges at the same condition as the current industry policy performance. A novel Performance-Based Inspection Planning (PBIP) protocol is introduced to demonstrate where inspections should be focused to monitor bridges in areas susceptible to more severe deterioration whilst easing inspection efforts on those in milder areas of deterioration, improving operational efficiency.

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List of Abbreviations

AASHTO	American Association of State Highway and Transportation
AI	Artificial Intelligence
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
BBN	Bayesian Belief Network
BPM	Backward Prediction Model
BCMI	Bridge Condition Marking Index
BMS	Bridge Management System
CBR	Case-Based Reasoning
CPN	Coloured Petri-Net
CPT	Conditional Probability Table
CPU	Central Processing Unit
CUDA	Compute Unified Device Architecture
DAG	Directed Acyclic Graph
DBN	Dynamic Bayesian Network
EMGTPA	Equivalent Million Gross Tonnes Per Annum
FHWA	Federal Highway Administration
FLOPS	Floating-Point Operations Per Second

GA	Genetic Algorithm
GPGPU	General-Purpose Graphics Processing Unit
GPU	Graphics Processing Unit
IDE	Integrated Development Environment
LEF	Local Environmental Factor
MC	Monte Carlo
MLE	Maximum Likelihood Estimator
MOGA	Multi-Objective Genetic Algorithm
MPH	Miles Per Hour
MTTF	Mean Time to Failure
NR	Network Rail
NSGAII	Non Sorting Genetic Algorithm II
ORR	Office of Rail Regulation
PCIe	Peripheral Component Interconnect Express
PBIP	Performance-Based Inspection Planning
PN	Petri-Net
PRNG	Pseudo Random Number Generation
RAM	Random Access Memory
SCMI	Structure Condition Marking Index

SIMT	Single Instruction, Multiple Thread
SMX	Next Generation Streaming Multiprocessor Unit
SevEx	Severity Extent Rating
TOC	Train Operating Companies
TPM	Transition Probability Matrix
TRM	Transition Rate Matrix
WLCC	Whole Life-Cycle Costing

Research Outputs

The research in this thesis was used in the development of the following scientific outputs. These have been presented in two sections: 1) papers destined for journals and 2) work destined for conferences.

Journal Papers

- Yianni, P. C., Rama, D., Neves, L. C., Andrews, J. D., Castlo, D. A Petri-Net-based Modelling Approach to Railway Bridge Asset Management. *Structure and Infrastructure Engineering*, 2016, DOI: 10.1080/15732479.2016.1157826.

- Yianni, P. C., Neves, L. C., Rama, D., Andrews, J. D., Dean, R. Incorporating Local Environmental Factors into Railway Bridge Asset Management. *Engineering Structures*, 2016, DOI: 10.1016/j.engstruct.2016.09.038.

- Yianni, P. C., Neves, L. C., Rama, D., Andrews, J. D. Incorporating Variability into Railway Bridge Asset Management [Submitted]. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering.*

- Yianni, P. C., Neves, L. C., Rama, D., Andrews, J. D. Accelerating Petri-Net Simulations using NVIDIA GPUs and CUDA [Submitted]. *European Journal of Operational Research.*

- Yianni, P. C., Neves, L. C., Rama, D., Andrews, J. D., Staden J. A GPGPU-Accelerated Hybrid GA approach to Optimise Inspection Policies for Railway Bridge Asset Management [To be Submitted]. *Journal of Bridge Engineering.*

Conferences

- Yianni, P. C., Neves, L. C., Rama, D., Andrews, J. D. Analysing Local Environmental Factors affecting Concrete Railway Bridge Deterioration. *Young Researchers' Conference, Institution of Structural Engineers*, 2016.

- Yianni, P. C., Neves, L. C., Rama, D., Andrews, J. D. High Performance Calibration of a Bridge Asset Management Model. *High Performance Computing Conference*, 2016.

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- Yianni, P. C., Neves, L. C., Rama, D., Andrews, J. D. Quantifying the Impact of Variability in Railway Bridge Asset Management [Submitted]. *International Symposium on Life-Cycle Civil Engineering, IALCCE2018.*

- Yianni, P. C., Neves, L. C., Rama, D., Andrews, J. D. Using Petri-Net Modelling for a Data-Driven Approach to Bridge Management and Safety [Submitted]. *International Association for Bridge Maintenance and Safety, IABMAS 2018.*

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Chapter 1

Introduction

Asset management has become a topic of intensive research in modern times. To be able to reach this stage of management, development had to begin with the homogenisation and standardisation of legislation. It could be argued that this was achieved with design standards: British Standards, Eurocodes and the International Organization for Standardization. Once all assets were being built to the same quality, then the focus could turn to their usage. One of the most popular techniques in asset management is using the Whole Life-Cycle Costing (WLCC) which accumulates the cost of the asset over the given time-scale. The most basic way of understanding WLCC is to consider two different maintenance procedures: M_A and M_B, where M_B costs twice as much as M_A. If M_B was unable to keep the asset in good condition for twice as long as M_A it would be financially inefficient. WLCC is designed to provide a quantitative output to the cost of asset operation and maintenance over a given time.

The railway is intrinsic to the UK transport sector, however much of the infrastructure is aged and requires regular maintenance. This maintenance, in turn, means that railway managers incur huge costs to maintain their portfolios of infrastructure. Railway infrastructure is critical to the smooth operation of the system. As well as having to deal with an age-

ing population of assets, the pressure to maximise budget performance is overwhelming. With the release of the Rail Technical Strategy (RTS), it seems that the demand on railway support structures will increase significantly; making the management of railway structures even more difficult (Technical Strategy Leadership Group (TSLG), 2012). This means an effective understanding of the assets is critical to be able to manage them successfully.

1.1 Background

The situation with many modern organisations is that budgets are being severely reduced. It is difficult to know which projects show promise and which projects should be scaled back to help relieve budgetary constraints. Focusing this down to an organisation that manages infrastructure, it can be difficult to know which assets should be upgraded, maintained at their current level or left to degrade naturally. There is a financial incentive to maintain any asset that will provide income or avoid penalty upon failure. In terms of the railway, income would come in the form of infrastructure usage by the Train Operating Companies (TOC) and penalties would come from the Office of Rail Regulation (ORR).

Network Rail (NR) is the UK's largest railway infrastructure owner and operator. According to their latest annual report (Network Rail, 2015), of the £2,949m spent on renewals, expenditure on bridges totalled £551m which is close to one fifth of their total renewals budget. This cost must be justified to the ORR who regulate spending in 5-year control periods. The more accurate NR can be with their financial requests, the more likely the ORR are to allow the expenditure. One difficulty that NR have is that the British railway network was mostly built in the Victorian Era (Network Rail, 2010a) and requires intensive maintenance and therefore, capital. Figure 1.1 shows the proportions of different bridge construction

eras. It can be seen that the vast majority of bridges were constructed in the period between 1850 and 1900.

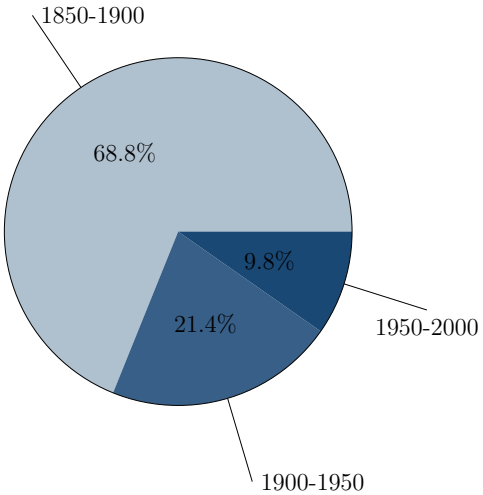


Figure 1.1: Proportions of railway bridge construction era (Network Rail, 2010a).

To be able to maintain an ever ageing population of railway structures with a continually tightening budget is a difficult task. If one were able to model the deterioration, inspection and maintenance effects of a typical railway bridge, then an effective decision support tool could be created which would help to maximise budget performance whilst maintaining the safety threshold of the network. It is therefore beneficial to infrastructure civil structures asset managers that a model is created which can support decision making including accounting for the long-term benefits as well as short-term gains.

1.2 Aims and Objectives

The overall aim of the research being presented in this thesis is to develop an approach for decision-support tools for the railway bridge asset managers. The objectives which support this aim are:

- to develop a mathematical railway bridge model that is calibrated

with historic data, industry guidelines on inspection and maintenance and expert opinion.

- investigate local factors which affect bridge deterioration and evaluate the impact of each factor with regards to deterioration, inspection and maintenance and ultimately, management.
- to ascertain if variability in the processes and practices around bridge management is significant and the impact of that variability on the WLCC.
- to use the latest advancements in computing technology to make sure that the decision support tool is rapid in its computation to encourage adoption.
- to perform optimisation of the inspection policies using the model to ascertain if the industry standard policies can be improved upon in both the overall WLCC and the condition of the assets.

A significant challenge is to be able to predict structural deterioration. There are already industry guidelines (Network Rail, 2012c) on the thresholds to inspect and maintain structures, but there is limited understanding of how structural defects develop and evolve over time. Additionally, certain defects are more or less likely to lead to other defects. Different elements will deteriorate in different ways and understanding the trends in behaviour is integral to predicting future deterioration.

1.3 Thesis Outline

The structure of the thesis follows the following outline:

Chapter 1 This chapter contains the introduction, including the background to the problem and the aims and objectives of the re-

search project. It identifies the main organisations managing railway bridges and their organisational perspective.

Chapter 2 This chapter begins with an introduction to fundamental aspects of asset management including information about WLCC. It then discusses and compares current Bridge Management Systems (BMSs) starting with the pioneers in the field and moving to more recent BMSs. This chapter includes information about the NR BMS as well as their policies on inspection and maintenance work.

Chapter 3 This chapter investigates approaches to modelling with particular focus on those used for BMSs. Stochastic modelling approaches are the primary focus including the traditional Markov modelling approach as well as a new modelling approach that is becoming increasingly popular: Petri-Nets (PNs). The advantages and disadvantages of these modelling approaches are discussed in reference to them being utilised for bridge asset management.

Chapter 4 This item details the railway bridge model which has been developed in this research project. The chapter begins with a discussion about the data source and data cleansing. It then follows on to describe each of the modules of the model that create the model in detail. Discussion is then focused on the calibration of the modules including a novel approach to the deterioration calibration. Finally, the chapter closes with sample model outputs including the analysis of the outputs.

Chapter 5 This chapter describes the investigation into the factors which affect railway bridge deterioration. A number of factors are analysed and the ones which are found to be key are investi-

gated further. Each of the key factors are built into the railway bridge model and financial comparisons are performed to find out which factors are the most crucial for railway bridge managers.

Chapter 6 This chapter looks into the sources of variability in the bridge management processes and practices. This includes misdiagnoses of element defects, imperfect repairs and rehabilitation cost variability. These are analysed and incorporated into the railway bridge model to investigate their effects on the overall system including the operational and financial impacts.

Chapter 7 This chapter describes a state-of-the-art computational development which has been used to dramatically decrease the time required for the model to execute. The chapter provides methodology to convert a traditional PN model simulation algorithm into one specifically designed for General-Purpose Graphics Processing Units (GPGPUs).

Chapter 8 This chapter provides optimised inspection policy results to give advice on the best way to manage railway bridge assets. It uses the results of all the previous chapters: the railway bridge model is used as the foundation and built upon using the factors affecting deterioration and the system variability. This is then processed in a hybrid evolutionary algorithm approach which uses a combination of the state-of-the-art hardware along with more traditional computing techniques.

Chapter 9 This is the final chapter and draws conclusions made on the other chapters, as well as the overall aim of the project. This chapter ties together the others as well, as drawing the research project to a close.

Chapter 2

Bridge Asset Management

2.1 Asset Management

Asset management is an aspect of increasing importance in business. Asset management encompasses many aspects and has an impact on a broad range of businesses. The body who created the ISO 55000 standard, the Institute of Asset Management (IAM), define asset management as the "co-ordinated activity of an organization to realize value from assets" (British Standards Institution, 2014). The assets being considered in this research are railway structures, primarily focusing on railway bridges. In civil engineering this phrase can be interpreted as an effective collaboration between those who inspect the structures, those who analyse the inspection data and those who use it to make decisions regarding rehabilitation. Collaboration between these parties should allow more effective management of assets which should result in reduced risk, improved condition and a more efficient use of budgets. The IAM define an asset as "an item, thing or entity that has potential or actual value to an organization" (British Standards Institution, 2014). There are many advantages of employing asset management in organisations; some of the main advantages an organisation can gain from effective asset management are:

- Improving budget performance without reducing asset reliability through the use of optimisation.
- Improved monitoring by focusing inspections on assets at higher risk of defect development.
- Understanding the sources of variability in the system with a view to control them.

2.1.1 The Art of Effective Planning

Asset management often involves balancing the performance, costs and risks associated with an asset. Performance in this regard refers to the condition of the asset. A policy which aims to maximise asset condition will also increase expenditure. A policy which tries to minimise expenditure will also impact on the asset condition which will, in turn, increase the amount of risk. It can be understood that there is an optimal point to balance the costs against the benefits. This could be extrapolated so that each individual asset or groups of assets has its own balance and therefore, its own optimal position. Different groups of assets will be subjected to different environmental stressors, different operational demands and different maintenance regimes. Therefore, each group of assets will have varying levels of acceptable risk and budget allocation which needs to be optimised. Figure 2.1 shows the financial consequences of the balance between different attributes.

2.1.2 Whole Life-Cycle Costing (WLCC)

WLCC is an extension of the factors discussed above by adding a time dimension to Figure 2.1. This means that to effectively manage an asset the condition, expenditure and risk has to be balanced over the lifetime of the asset.

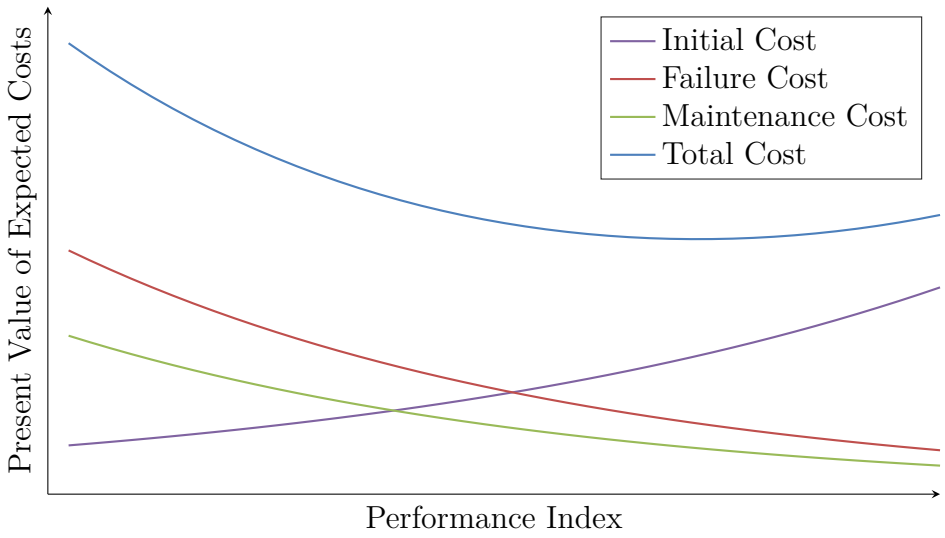


Figure 2.1: Balance and optimal solution between different asset attributes (adapted from Frangopol (2011)).

A policy which encourages frequent minor repair may improve the condition of the asset, but the organisation and capital required may mean that it is more efficient to let the asset deteriorate to a worse state and perform fewer major repairs. With regards to railway assets, Network Rail (NR) must pay fines/penalties to both the Train Operating Companiess (TOCs) and the Office of Rail Regulation (ORR) for under-performing assets or possession of assets to perform rehabilitation, resulting in additional costs from both excessive deterioration and frequent maintenance.

Figure 2.2 depicts the asset condition of a typical maintenance policy. As the condition of the asset worsens over time, it will approach a minimum acceptable safety threshold. An intervention would be carried out which improves the condition of the asset accordingly. In this example, it returns the condition to as good as new condition. It is possible to schedule inspections more frequently to monitor more closely the condition of the asset, however this would increase expenditure and face possible possession fines.

In a discussion with a Whole Life Costing Manager at NR, an interesting

paradox was considered which was that, typically, the more heavily used an asset, the quicker the deterioration occurs which means that maintenance is required sooner. However, because the asset is heavily utilised, there is less opportunity to perform rehabilitation which enables further deterioration of the asset.

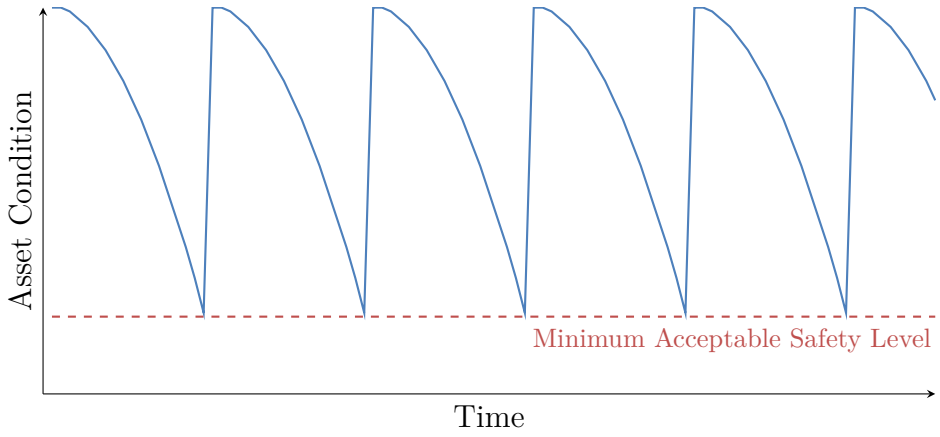


Figure 2.2: Intervention during the life cycle of an asset showing the minimum acceptable safety threshold.

2.2 Bridge Management Systems (BMSs)

Due to the significant cost of maintaining a portfolio of bridge assets, and the consequences of failure, most large bridge owners have either implemented existing BMSs or developed their own. Different bridge management organisations have different needs and work to different regulatory frameworks and so there are a wide variety of management systems, with varying levels of sophistication. In most cases, they have been developed by national or regional owners and may only consider bridges, or be flexible enough to accept other asset types, e.g. embankments.

A large group of BMSs are currently in use in Europe, North America and Japan. These are usually developed by managing agencies or outsourced to external consultants. Being fundamentally commercial applica-

tions, the existing literature regarding these systems is limited, and often obsolete as improvements are regularly implemented, as shown in Figure 2.3. A list of currently used BMSs, as well as a short description of the capabilities of each system, is provided in Mirzaei et al. (2014). The following section will describe some of the key properties of BMSs, identifying systems which are particularly relevant due to the widespread usage, innovation or interest to the present research.

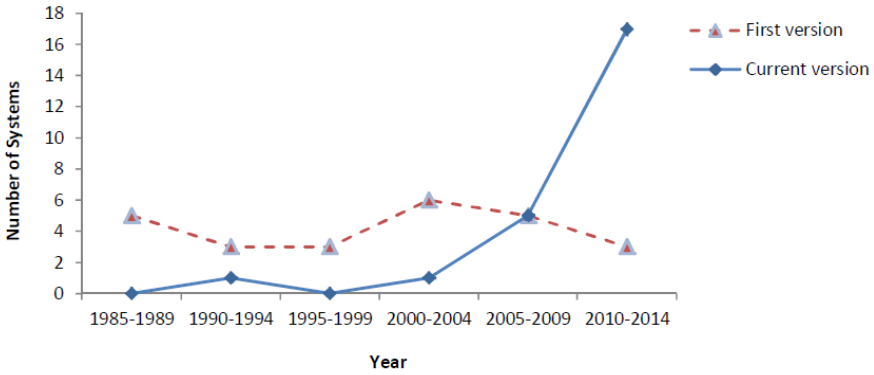


Figure 2.3: A comparison of the number of BMSs which are in their first version to those which have been updated (Mirzaei et al., 2014).

2.2.1 Historical Development

As with most areas of civil engineering, the development of management systems was triggered by an accident. In December 15, 1967 the Silver Bridge crossing the Ohio River collapsed during the evening rush hour, resulting in the loss of 46 lives and nine injuries. The subsequent investigation showed that bridges were not being inspected in a manner that produced reliable results. As a consequence, the US Congress approved the National Bridge Inspection Standards (NBIS) in 1968. This legislation defined policies regarding frequency of inspections and personnel requirement to conduct the inspections. Inspectors were trained, forms completed and reports were submitted to the Federal Highway Administration (FHWA).

For years, the information gathered in the NBIS served only to define if emergency repairs were required and although the system had significantly increased the safety of users, had little impact on medium and long term bridge usage (Lichtenstein, 1993).

In the mid to late 1980's a set of research programs were funded by FHWA and the National Cooperative Highway Research Program to make better use of the information available, allowing prediction of future performance and of budget requirements. The FHWA project continued with the development of the Pontis bridge management system. The NCHRP research continued with the development of the BRIDGIT BMS. Both systems shared a set of characteristics which are now standard in most BMSs, including the use of visual inspections as the main source of information on bridge performance and Markov deterioration models to perform optimization to maximize the safety and minimize the WLCC. Although originally implemented in the 1990's, both systems have undergone significant improvements. However, the fundamental properties and mathematical modelling and optimization procedures have not been significantly modified (Small et al., 1999).

2.2.2 Fundamental Framework

Mirzaei et al. (2014) discusses that the fundamental components of a BMS are: 1) asset register; 2) inspection and maintenance records; 3) predictive deterioration models and 4) intervention strategies. The first component is a database or inventory which includes fundamental information on all bridges in a network, including: location, use, materials, geometry, age, etc. Ideally, the inventory should contain design and as-built drawings, allowing a better understanding of any defect or alteration. This module is usually a very stable part of the BMS, with new information being included only after the construction of a new bridge, large repair actions or inclusion of

new road segments in the network. The second component of a BMS is an inspection and maintenance database, containing the results of all inspections performed on each bridge, as well as any maintenance actions. The level of detail of this database varies significantly amongst BMS. Usually bridge assets are divided into components, and each component is given a score characterizing its deterioration state and, indirectly, its performance. The condition state was characterized fundamentally using visual inspections, resulting in a score using a discrete scale. This method is still present in most current BMSs. Mirzaei et al. (2014) assessed a total of 25 BMSs from Europe, Asia and North America. All the systems analysed used a condition index approach, resulting from visuals inspections. The third component refers to the deterioration models, allowing the prediction of the remaining life of each component or bridge or, alternatively, the prediction of evolution of performance over time. A wide range of models have been implemented to achieve these objectives, with Markov Chains being the most commonly used approach. This component is fundamental in this research, and will be discussed in greater detail. The fourth component presents the results of the intervention strategy optimisation. Considering that one of the primary objectives of a BMS is to minimize the requirement maintenance costs while keeping structures safe and serviceable, many systems contain detailed information and models to compute the costs associated with maintenance actions. According to Mirzaei et al. (2014), of the 25 BMSs evaluated, 24 include some method to estimate cost of maintenance actions, while the most advanced systems include the cost of increased risk of traffic accidents, loss of time and environmental costs and inspection costs. This component can be combined with an optimization procedure to identify strategies which lead to minimum cost and maximum performance. Although these are the fundamental blocks of a BMS, many current systems only implement part of this framework. In fact, the process of developing a BMS is usually relatively slow, as a long record of inspec-

tions is required before a deterioration model can be reliably fitted, and extensive data and experience of maintenance actions is required before a robust maintenance consequence can be proposed (Mirzaei et al., 2014).

2.2.3 Current Bridge Management Systems (BMSs)

The Organisation for Economic Co-operation and Development (OECD) define a BMS as a tool aiming at helping "highway and bridge agencies in their choice of optimum improvements to the bridge network that are consistent with the agency's policies, long-term objectives, and budgetary constraints" (Organization for Economic Co-operation and Development (OECD), 1992). Current BMSs focus on highway bridges for historical reason; however, they are similar enough to railway bridges that the techniques can be used interchangeable. Notable countries that use BMSs are the US, Canada, Switzerland and Japan. There are a number of key BMS software solutions that have dominated over time. Bridgit (Hawk, 1999) was one of the earliest solutions which was then superseded by Pontis (Golabi and Shepard, 1997) which became part of AASHTOWare Bridge Management suite. The following sections describe how these BMSs work, their differences and limitations.

2.2.3.1 Brigit

Bridgit was developed in 1985 by the National Cooperative Highway Research Program (NCHRP) and the National Engineering Technology Corporation (Hawk, 1999). The software contains a number of packages that are designed to: hold a database of asset information, contain a record of the condition of those assets, display the feasible intervention options, predict the future deterioration of the assets and finally predict the cost of the interventions. The database holds information about the asset including a breakdown of each minor element and its condition. The assets are ranked

based on a cost-benefit ratio and prioritised for the maximum benefit to least cost. This information is used in a two stage repair strategy. The first set of repairs that are scheduled are to maintain the bridge to a certain safety level. The second scheduled repair is to improve the service on the road. The deterioration model is based on the Markov approach which will be explained in Section 3.4.2.

There are some limitations to the Brigit BMS software. Firstly, Mohamed (1995), identified that the structure of the optimisation process can lead to some factors not being considered. The optimisation considers the rehabilitation and replacement projects differently when analysed with the improvement projects. They argue that both rehabilitation and replacement projects have the same effect on the network and the separation of them creates an error in the costs. Secondly, Ryall (2001), critiqued the ranking system that Brigit uses to prioritise interventions as the incremental cost-benefit ratio does not utilise funds optimally. Additionally, the focus of the software seemed to be maximising budget performance with less consideration about safety or service quality impacts.

From the literature, it is clear that Brigit introduced a much needed decision support tool for the time, however it had several flaws that meant it was superseded soon after.

2.2.3.2 AASHTOWare Bridge Management

Pontis was introduced in 1992 as a rival to Brigit. The project was funded by the American Association of State Highway and Transportation (AASHTO). The advantage of the Pontis software was that it was meant to link into data from the U.S. FHWA. The FHWA had previously released guidelines about the criteria and performance monitors of bridges known as the National Bridge Inventory System (NBIS) which Pontis also integrated (Golabi and Shepard, 1997). Even though Pontis was developed after Brigit, they both use the same Markov-based modelling technique and prioritisa-

tion processes which means that they suffer from similar drawbacks.

The AASHTO then amalgamated Pontis, Virtis and Opis into a piece of software known as BRIDGEWare. Virtis is a structural analysis program that calculates the load capabilities of bridges. Opis is a material analysis tool that can create feasibility reports on different bridge designs in different materials. This software was then repackaged under the AASHTOWare line of products and is now known as AASHTOWare Bridge Management. The United States Department of Transportation reports that, as of 2008, AASHTOWare has been licensed to 40 US states and a number of other organisations. It remains the most widely used of all the BMSs employed (Golabi and Shepard, 1997).

2.2.3.3 Swiss Bridge Management System (BMS)

In 1992 the Swiss Federal Highways Office (SFHO) began the development of their own BMS, known as KUBA (Roelfstra et al., 2004). It is based on the underpinnings of the AASHTOWare BMS, however, it contains more advanced project level features. One of the main features of the BMS is its ability to optimise the economic costs both considering the WLCC of the structure as well as the yearly network-level costs. It uses a number of modules that each perform a different task including: 1) retrieving the asset inspection data from the inventory (KUBA-DB), 2) using condition forecasting, based on the material type rather than the element type (KUBA-MS), 3) determining the appropriate maintenance action to be carried out on the element (KUBA-ST) and finally, 4) optimising the working program of the structure by balancing the WLCC with the structural safety (KUBA-RP). This process can take into account maintenance of groups of bridges as well as individual bridges to maximise the potential optimisation benefit (Ludescher and Hajdin, 1999).

KUBA uses five condition states which range from 1, which is a "Good" condition with little or no visible damage, to 5 which relates to a condition

causing alarm due to a reduction in safety. Elements in condition state 5 require urgent repair due before the next regular inspection (Adey and Hajdin, 2011). The condition of a structure is reported using the severity and extent of the defect; each of the 5 condition states mentioned have a further 5 extents which relate to the percentage of the element that is suffering from the defect. The underlying deterioration model is Markov-based and due to the condition forecasting being performed on the element material rather than the element type, the number of Markov states is reduced which simplifies the model (Ludescher and Hajdin, 1999). Therefore, the resulting Markov model has 25 states in total (Adey and Hajdin, 2011). The BMS is designed to encourage strengthening and preventative maintenance over corrective works; this is achieved with the comparatively high cost of performing repairs on assets in condition state 5 (Hajdin, 2008).

The effectiveness of interventions is also considered in the model, which has either been derived from historical data or expert opinion. Interventions are available when the element is in the third condition state or worse. The effectiveness vectors indicate the probability of the condition that the element would return to after a typical intervention of this type. Each modelled intervention has a deterministic cost, irrespective of the effectiveness of the work being carried out. Apart from elements composed of metal or composites, a "Do Nothing" approach is assumed for all elements in condition states 1,2 and 3.

An interesting addition to the KUBA is the inclusion of influence indicators which are applied to sections of structural elements known as "segments". Examples of deterioration influence indicators include weathering, chemically aggressive contaminants and chloride exposure (Roelfstra et al., 2004; Adey and Hajdin, 2004). The use of these indicators is applied in the form of a matrix which acts upon the Markov model and can hasten deterioration of the element(s) (Ludescher and Hajdin, 1999).

Although KUBA considers bridge modelling on an asset and sub-asset

level, many of the optimisation considerations are at a network level, which benefits its adoption with bridge portfolio managers. This aspect is evident in two ways, the first is that when interventions are being considered, a cost-benefit ratio is calculated for both the asset and at a network level. This should help optimise the interventions over the portfolio in the long-term. The second is that the model considers "Agency Rules" to offer more practical recommendations to bridge portfolio managers. One example would be operational considerations where more than 5% of the bridge must be in a poor condition state to maximise network level benefit (Adey and Hajdin, 2011).

Overall it seems that KUBA introduced a number of useful features for bridge portfolio managers including considering deterioration and the factors affecting deterioration. Adey and Hajdin (2004) mentions, however, that KUBA only considers agency costs and ignores user/societal costs, including the increased risk with bridges in poor condition.

2.2.3.4 Ontario Bridge Management System (OBMS)

Ontarios Ministry of Transportation (MTO) analysed which widely available system, Pontis or Brigit, would be more suitable for them to use. Unfortunately, the environmental conditions in Canada meant that neither Pontis nor Brigit were suitable. In 1998 the MTO decided to create a bespoke BMS with the same creator of Pontis, Thompson P. The key difference between the OBMS and Pontis/Brigit is that the OBMS was designed to be optimised for safety, economics and network performance whereas Pontis and Brigit were designed primarily to maximise budget performance. The OBMS ties in with other Canadian guidelines for asset inspection. These guidelines suggest that the element material and type are recorded as well as the defect severity and extent. These conditions are then converted to a representative percentage and then placed into categories with other elements of a similar condition state. There are four

condition categories: Excellent, Good, Fair, and Poor. The OBMS uses a Markov-based model to predict future condition, which is the same as Pontis and Brigit (Thompson and Kerr, 2001).

The OBMS includes a unique intervention module. A database holds the information of the condition of each element and then a set of feasible intervention strategies is created. From those, an optimisation is executed with a Markov condition prediction model, to deduce which interventions are best for that element. Then the list of recommended interventions is run through a cost-benefit analysis to allow the bridge manager to see which intervention performs best in terms of financial performance (Thompson, 2001). This information can then be fed into the network-wide overview and each feasible intervention can be analysed from a network perspective. This is one area where the OBMS excels, compared with the established Pontis/Brigit software.

Thompson (2003), states that the OBMS has been hindered by some of the same shortcomings as Pontis/Brigit, with a lack of user costs in the model. Additionally, in real-world use, the OBMS has only been partially utilised. The database modules have been taken advantage of to store asset information, however the intervention module was not seen as effective as traditional engineers judgement.

2.2.3.5 Danish Bridge Management System (DANBRO)

Branco and de Brito (2004) discuss DANBRO (DANish Bridges and ROads) as managing 2,500 bridges in Denmark, as well as 10,000 bridges in Thailand, in addition to managing smaller portfolios in Saudi Arabia, Mexico, Colombia, Honduras, Croatia and Malaysia. Development began in 1988, issued by the Road Directorate of Denmark. The Road Directorate realised that existing bridge databases contained vast amounts of unused data that incurred significant cost to keep uo to date (Ryall, 2001). DANBRO was developed as a BMS designed by bridge engineers to serve bridge engineers

and is very popular for that reason. DANBROs wide adoption has been attributed to the flexibility of the system since, as explained by Das (1999), it is not realistic for an organisation to change its company policies and procedures to suit a new piece of software.

Lauridsen and Lassen (1999) explains that DANBRO released a set of inspection guidelines with a condition rating from 0-5, where 0 represents elements with no damage and 5 which represents elements which have exhibited complete failure. The guidelines also request that the inspector identifies the type of repair work required along with a cost estimate, the urgency of the repair and the next inspection interval. This requirement is unusual and not often seen in other BMSs guidelines. The inspection data is then used to generate an estimate of the bearing capacity, which this system uses as the performance indicator (Branco and de Brito, 2004).

2.2.3.6 Network Rail (NR) Bridge Management System (BMS)

NR is the largest owner of railway bridge assets in the UK (PCC, 2013). Therefore, their asset management policies and processes are the most relevant to this research. NR maintains a large portfolio of bridges across the UK. They have laid out asset policy documents for each type of bridge which details the inspection and maintenance policies. The majority of the policies are risk-based and are designed to prevent an increase in risk to passenger safety (Network Rail, 2012c). NR break down their bridges into a number of elements in a hierarchical manner. The "Major Elements" are used to describe sections of the bridge e.g. deck. The use of this level is mostly as a grouping system. The next level is the "Minor Elements", which is the level at which intervention decisions are made.

A further level is evident in the inspection data but not mentioned in the policy documents. This level was created to break down sizeable Minor Elements for ease of inspection. In this research these elements are known as "Sub-Minor Elements".

2.2.3.7 Network Rail (NR) Condition Monitoring

NR inspect each Sub-Minor element of each bridge and give it a rating according to its condition. The ratings of elements are based on Severity Extent Rating (SevEx). Each time an element is inspected, its condition is recorded. For concrete bridges, the example used in this research, the SevEx ratings go from A1 (perfect condition) to G6 (permanent structural damage). The first character refers to the type of defect and the second refers to the extent of the defect, the full SevEx ratings can be seen in Table 2.1. The most common defects seen in concrete elements are cracking and spalling, Nielsen et al. (2013) found them to be as high as 89.9% of all concrete defects.

Table 2.1: SevEx defects for concrete structures (Network Rail, 2012c)

Severity	Defect Definition
A	No visible defects
B	Surface damage, Minor spalling, Wetness, Staining, Cracking <1mm wide
C	Spalling without evidence of corrosion, Cracking $\geq$ 1mm wide without evidence of corrosion
D	Spalling with evidence of corrosion, Cracking $\geq$ 1mm wide with evidence of corrosion
E	Secondary reinforcement exposed
F	Primary reinforcement exposed
G	Structural damage to element including permanent distortion
Extent	**Definition**
1	No visible defects
2	Localised defect due to local circumstances.
3	Affects <5% of the surface of the element.
4	Affects 5%-10% of the surface of the element.
5	Affects 10%-50% of the surface of the element.
6	Affects >50% of the surface of the element.

The Structure Condition Marking Index (SCMI) is a system designed to give a global score to an asset based on weighted element scores. Each of the elements marked with the SevEx system is given a numerical value which then composes the SCMI score. Table 2.2 contains the information

to convert a SevEx score to a numerical value. Equations 2.1, 2.2 and 2.3 are then used to calculate the SCMI score.

Table 2.2: SevEx conversion matrix to a numerical score, adapted from Network Rail (2010e)

		Extent					
		1	2	3	4	5	6
Severity	A	0.0					
	B		1.0	2.0	2.5	3.0	3.5
	C		2.0	3.5	4.0	5.0	6.0
	D		3.0	4.0	5.0	6.5	8.5
	E		4.0	5.0	7.0	8.5	9.0
	F		5.0	7.0	9.0	9.5	10.0
	G		5.0	8.5	9.0	9.5	10.0

$$Minor\ Element\ Score = 100 - (10 \cdot Max\ SevEx) \tag{2.1}$$

$$Major\ Element\ Score = 100 - ((\sum(E_f \cdot Max\ SevEx)/N_{min}) \cdot N_f) \tag{2.2}$$

$$Normalisation\ Factor = N_f = 100 - (\sum(E_f \cdot 10)/N_{min}) \tag{2.3}$$

where Ef is the element weighting; $SevEx$ is the Severity Extent value; $Nmin$ is the number of minor elements in the major element and Nf is the normalisation factor. It can be seen from the equations that an asset in perfect condition scores 100 and as the condition worsens, it gets closer to 0. However, by using the SCMI score, the details of the type of defect and extent are lost compared to using the SevEx score directly.

The current NR policies lay out guidelines for when inspection should be scheduled. NR uses two types of inspections. The first, detailed inspections, are performed within touching distance. Each of the elements are inspected

and the SevEx score recorded. The frequency of detailed inspections are dependant upon the asset condition. The second, visual inspections, are carried out annually. An inspector uses the last detailed inspection to make sure that no major changes to element condition have occurred. No scoring is carried out on visual inspections. Henceforth, any reference to an inspection is referencing detailed inspections.

The condition of the element is converted from the SevEx score, used during inspections, to the SCMI score. Table 2.3 details the corresponding risk category relating to the SCMI score. From there, Table 2.4 details what the appropriate inspection interval would be for that particular element.

Table 2.3: Table extract showing the risk category according to the SCMI, the condition of the element (Network Rail, 2010c). C is the condition of the element in the respective metric.

Attribute	Risk Category		
	Lower	Medium	Higher
SCMI overall score	$75 < C \leq 100$	$45 < C \leq 75$	$0 \leq C \leq 45$

Table 2.4: Table extract showing the typical intervals between inspections for concrete bridges in different risk categories (Network Rail, 2010c). The terms "Lower", "Medium" and "Higher" refer to the risk category.

Primary Material	Maximum Interval between Detailed Examinations (Years)		
	Lower	Medium	Higher
Cast in-situ reinforced concrete	12	6	3
Pre-cast concrete	12	6	3
Pre-tensioned concrete	12	6	3

2.2.3.8 Network Rail (NR) Maintenance Policy

The current NR policies also lay out guidelines for when maintenance should be scheduled. This is decided upon by an index number known as SCMI. An A1 SevEx condition would relate to an Bridge Condition Marking Index (BCMI) of 100 and a G6 SevEx condition would relate

to an SCMI of 0. The thresholds for the different maintenance actions are given in terms of SCMI (Network Rail, 2010b). The two major intervention types mentioned in the policies are "Repair" and "Replacement". The fundamental condition that all elements must meet or exceed is known as the "Basic Safety Limit" which varies for different materials. Elements which have a condition which is below the "Basic Safety Limit" are scheduled for replacement.

Whilst exploring the database of inspections, it was evident that there were repair works carried out above the Repair condition threshold given in the policy. In discussions with the NR Principal Engineers, it became clear that there were two reasons for intervention: 1) the elements that had breached the NR Repair condition threshold and 2) the elements that were above the Repair threshold but the local maintenance team had decided they should intervene. Therefore, there are three types of intervention. In this research, the "Repair" threshold mentioned in the NR policies will be known as "Major Repair" and interventions carried out above this threshold will be known as "Minor Repair"; the final intervention remains as "Replacement". SevEx condition A1 is the only condition which is not assigned to a repair type, as this is the perfect condition.

Table 2.5 shows the consolidated information from Network Rail (2012a) for concrete elements. The "Basic Safety Limit" is set at SevEx score $F4$ and the threshold to carry out Major Repair is $D3$. The equivalent SCMI scores are also provided in the table.

Table 2.5: Table consolidating the maintenance policy information from Network Rail (2012a). C in this instance is the condition of the element in the respective metric.

Threshold	Minor Repair	Major Repair	Replacement
SevEx	$A1 < C < D3$	$D3 \leq C < F4$	$C \leq F4$
SCMI	$100 < C < 70$	$70 \leq C < 40$	$C \leq 40$

2.2.3.9 Network Rail (NR) Tier 2 Model

NR have developed a number of BMSs over time, each a development over the previous one. The most recent BMS is known as the "Tier 2 Structures Model". The BMS was originally created from a sample set of 73 bridges of different material types and ages and then verified using another 243 structures to check the output (Network Rail, 2012b). The BMS uses the SevEx inspection data. Each of the SevEx scores is converted to a numerical value. Then, depending on bridge construction material, the numerical values are divided into condition states. These condition states are used to build the Markov model that predicts future deterioration. Tables 2.2 and 2.6 contain the information about how the SevEx score is converted to a numerical value and then the numerical value is converted to condition states for a metallic element. For each material the number of condition states is different (Network Rail, 2012c).

Table 2.6: Conversion of SevEx numerical scores to condition states, adapted from Network Rail (2010e)

Numerical Score	State No.
0.00	1
0.50	2
0.75	3
1.00	4
1.25	5
1.50	6
2.00	7
2.50	8
3.00	9
3.50	10
4.50	11
6.00	12

The Tier 2 model uses the Markov state transition probabilities to predict the future structural condition. This is then used with the WLCC module to output a series of graphs, an example of which can be seen in Figure 2.4. The graphs represent the WLCC over the lifetime of the asset,

the condition of the asset and the subsequent risk associated with the asset condition.

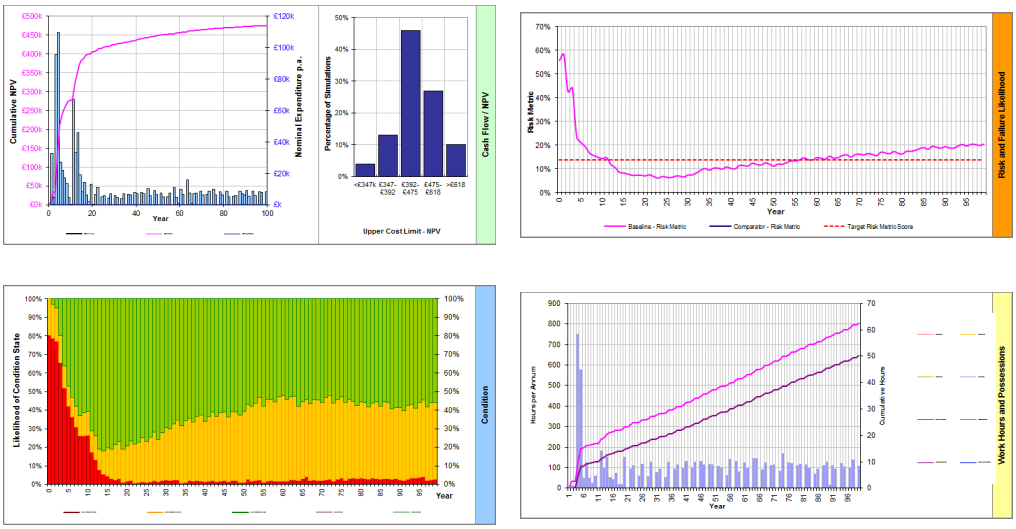


Figure 2.4: Sample output from NR Tier 2 model.

NR are one of the largest bridge owners in the UK (PCC, 2013) so they have a mature system of policies and practices to orchestrate inspections, maintenance and renewals across their structures. Their BMS predicts future deterioration of assets using a Markov Chain model. NR have developed a BMS system that currently revolves around their industry policies, but is moving towards a more modelling-centric approach.

2.2.3.10 Bridge Management in Europe (BRIME)

Often BMSs follow a similar framework but are calibrated differently according to the assets, policies and key features of each region. A project called Bridge Management in Europe (BRIME), attempts to provide a consistent framework between these countries. It should be stressed that BRIME is a bridge management framework and is not a BMS solution. The BRIME project is designed to encourage best practices for bridge management, however they do not offer a software system like traditional BMSs.

Their approach has been to analyse current BMSs and try to implement a homogeneous system of best practices. BRIME has identified that most of the current BMSs use a Markov approach to predict future condition. BRIME has also proposed this method with a 5-stage Markov chain. The current BMSs have a discrepancy with the inspection phase of the process, arguably the most important one is the inspection data is what the rest of the model is calibrated against. BRIME presents a comprehensive framework of inspection with varying levels of investigation from minor visual inspection to major invasive inspection. The inspection is both local and global in the sense that individual elements are inspected, as well as the structure as a whole. The result is a cumulative condition rating based on weighted averages for the whole structure, in addition to an individual score for each element.

BRIME is designed to have a more modern approach to prioritisation so it considers safety, durability, functionality and socio-economic issues as well as the traditional construction, inspection, maintenance, repair, failure, traffic and renewal. These factors are assigned a global weighting with an associated "cost". Then a standard cost-benefit analysis is used to compare different intervention options. BRIME has had some success in gathering data and expertise from certain European countries as seen in Figure 2.5, however adoption of the framework has been slow. BRIME was written from a client's perspective which means some of the inspection and intervention suggestions are difficult to implement in the real world. Furthermore, the changes to the current maintenance procedures would be drastic which slows corporate uptake.

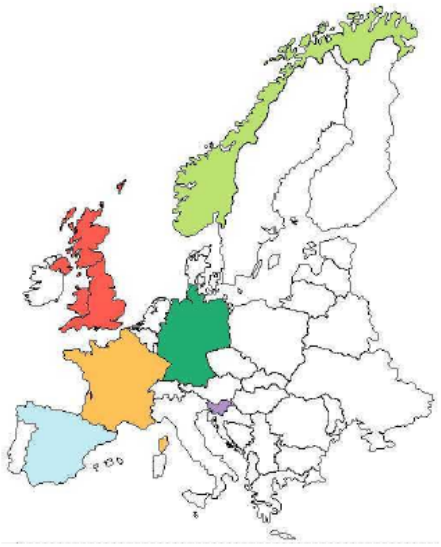


Figure 2.5: Map showing the countries participating in the BRIME project

2.2.3.11 Summary of Bridge Management Systems (BMSs)

Brigit pioneered the bridge decision support tool in the mid-1980's. It contained a database of all the assets and gave a future prediction of condition. It then provided intervention suggestions with a cost-benefit analysis. For the time, this decision support tool was state-of-the-art. However, it ignores certain costs and focuses too much on budget maximisation without enough consideration of other factors. Pontis was developed in the early 1990's with advanced networking features to collate data from the U.S. Federal Highway Administration. Pontis improved upon the scope of Brigit, but still used the same modelling and prioritisation techniques and therefore suffered from similar drawbacks. The Ontario Bridge Management System was developed in 1998 which had a more rigorous prioritisation strategy as it took account of safety and quality factors too. The adoption of this system was limited as although it took more factors into account, it still neglected key issues, like user cost. Finally, the NR BMS demonstrates a UK-based railway BMS approach. It uses the same severity and extent scores found in OBMS and the same Markov-based modelling approach

found in other popular BMSs.

2.2.4 Summary of Bridge Asset Management

The chapter introduced the fundamental aspects of asset management with a focus on the management of bridge assets. The current decision support tools known as BMSs were introduced. One of the most notable BMSs is Pontis, which was the first of the BMSs and has shaped the nature of subsequent BMSs over time. A more detailed review of a UK railway BMS was carried out, as it is the most relevant to this research due to the fact that it is specifically for railway bridges and the assets being managed are in the same region.

The next chapter will investigate the modelling techniques which underpin the BMSs. The significance of the BMSs is that they are the basis for the research with the modelling techniques affecting the approach taken to model the assets.

Chapter 3

Modelling Approaches and Techniques

Deterioration is a constant issue when managing assets as well as changes in demand of the infrastructure. With regards to structures, mathematical modelling can be used to predict the condition to some extent. This chapter concentrates on the types of modelling techniques used in the current Bridge Management Systems (BMSs) to predict structural condition. An overview of modelling techniques is presented and then the chapter focuses more on a description of two major stochastic modelling techniques: the established Markov and the more novel Petri-Net (PN).

3.1 Types of Modelling Techniques

There are many different modelling techniques used to model deterioration of civil structures. Mechanistic models are based on the use of fundamental mechanical models relating loads, material properties and consequences of deterioration (e.g. corrosion depth). Being a very granular methodology, the amount of data required to evaluate the life cycle performance of a complex asset, like a bridge, is not usually available and the cost

of gathering the required data is incomparable with the analysis of large asset portfolios. Furthermore, the uncertainty in several parameters influencing performance, in particular, the evolution of deterioration, leads to uncertainty levels incompatible with decision making over long periods of time. As a result, data driven approaches based on the deterministic and probabilistic curve fitting to existing data is usually preferred for medium to long term predictions of asset condition. Deterministic models do not include any probabilistic modelling which means that the same input will yield the same output. Furthermore, deterministic deterioration models for structures are difficult to define because the relationship between variables is often highly complex and difficult to prove with absolute certainty. A branch of deterministic modelling has developed into artificial intelligence modelling which uses much more complex relationships, but suffer from some of the same drawbacks. Stochastic models, on the other hand, use probabilities to determine the most likely outcome. They often use one set of data to fit the function and then test the results on another set of data to verify the model.

Table 3.1: The approaches to structural deterioration, adapted from Morcous et al. (2002b)

Category	Models
Mechanistic models	Mechanistic models
Deterministic models	Straight line extrapolation models Regression models Curve-fitting models
Stochastic models	Markov models Petri-Net (PN) models Bayesian Belief Network (BBN) models
Artificial Intelligence (AI) models	Artificial Neural Network (ANN) models Case-Based Reasoning (CBR) models

Models can be classified into a number of categories. The following are examples of different ways of classifying deterioration models. One of the

most straightforward classifications is that of linearity or non-linearity. If all the variables follow a linear relationship, then the model itself is known to be linear in its nature. Static and dynamic models are another classification category. Static models have fixed variables or transition times, for example, which means that results can be more predictable. Dynamic models allow for variables or transition times to change over time depending on other conditions and, consequently, increase the complexity of the analysis. Models can be either discrete or continuous. A discrete model will work in integer time steps and give a discrete result. Continuous models represent objects of an uninterrupted manner in time and/or performance measures. Deterministic and stochastic models are two distinct classification types. Deterministic models are designed to give a repeatable result with the same input. Stochastic, or probabilistic models, are designed to include randomness by using, for example, probabilistic distributions. Models can also be classified into mechanistic and empirical. Empirical models are derived from observation of systems, whereas mechanistic models break down a complex system into individual parts and solve each one in turn. For instance, it is possible to observe a structure and create an empirical model to predict its usable life without considering its material, environmental conditions or construction technique. The mechanistic approach is to analyse the materials, environmental conditions and construction technique and then predict the usable life of the whole structure without observing the structure in its actual configuration.

3.2 Mechanistic Models

Mechanistic models aim to describe deterioration at a high-level of detail at a small scale. Kayser and Nowak (1989) created a mechanistic model to identify the loss of capacity in steel members of bridges. It was identified by Komp (1987) that the relationship was exponential in nature so Kayser

and Nowak (1989) formulated the mechanistic Equation 3.1.

$$C = At^B \tag{3.1}$$

where A, B are parameters from regression analysis of the experimental data; C is the average corrosion penetration measured in microns. Based on this expression for corrosion, mechanical models can be used to estimate the strength of the structure and its safety.

Although mechanistic models have been used to predict the future performance of existing structures, the uncertainty in the future deterioration evolution significantly limits the usefulness of this approach. Extensive work has been developed aiming at predicting future performance of deteriorating structures. The works of Val and Melchers (1997) on reinforced concrete bridges are particularly relevant as it introduced a general framework for structural deterioration modelling which is used in a variety of other studies.

Morcous et al. (2010) states that mechanistic models are able to accurately predict degradation from various forms of defects such as corrosion, cracking and overstress. However, mechanistic models require vast amounts of data to be accurate. Additionally, the modelling technique is inefficient when being applied to a large set of structures with different materials, defects and conditions. Finally, to be able to use Mechanistic models, organisations may have to change their inspection procedures to gather more data, of new metrics, about the defects and inspect the defects more frequently. This could be operationally infeasible which limits the effectiveness of using Mechanistic models. The preferred modelling approach should be flexible enough to fit in with the existing practices of bridge management organisations.

3.3 Deterministic Models

Deterministic models assume that if all relevant data can be gathered, a precise and accurate prediction of the future performance can be computed. Deterministic models are so called because they can repeatedly determine the outcome from the same input. Morcous et al. (2002b), stated that there are three main types of deterministic model: straight line extrapolation, regression models and curve fitting models. Using linear extrapolation to model structural degradation has not been widely adopted. However, regression and curve fitting models have been used to model structural degradation.

3.3.1 Regression Model

Regression models often link two or more variables to describe a behaviour. The most basic form of this model uses a straight line slope and intercept to relate two variables. A classic form of this model is described in Shahin (2005), where it is used for bridge deterioration modelling:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon \tag{3.2}$$

where X_i is the age of structure i; Y_i is the condition rating of structure i; ε is the prediction error and β_0, β_1 are the regression parameters, intercept and slope of the line respectively. If a greater number of relationships were investigated, the equation can be expanded upon:

$$Y_i = \beta_0 + \sum_j \beta_i X_{i,j} + \varepsilon \tag{3.3}$$

where $X_{i,j}$ represents other variables such as material, location, environmental factors, etc. respecting to structure i. Jiang and Sinha (1989) stated that regression models of this type were not sophisticated enough to model structural deterioration and so a third-order polynomial was de-

veloped in the form of Equation 3.4 which is designed to better fit bridge deterioration:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \beta_3 X_i^3 + \varepsilon \tag{3.4}$$

where Y_i is the condition rating of bridge i and age X; X_i is the bridge age and ε is the error parameter.

This equation describes the relationship between the condition rating of the bridge, Y_i, and the bridge age, X_i. A flat S-shape is maintained due to the third order polynomial, however these types of models predict shorter asset lifetimes than other regression based models (Shiraishi et al., 1998). Therefore, its effectiveness as a long-term predictor of asset condition is limited, which is a necessary feature of a Whole Life-Cycle Costing (WLCC) model.

3.3.2 Curve Fitting Model

Curve fitting is defined as establishing a mathematical function that best describes the data. Often, the data is scattered in a general trend and so a curve must be manipulated to optimally fit the data. Sanders and Zhang (1994) improve upon Equation 3.4 by incorporating interventions. With the use of the curve fitting approach the authors were able to establish Equation 3.5:

$$Y_{(t)} = (1-A)(1-B)(1-C)\alpha_1 e^{\frac{-t}{\beta_1}} + A\alpha_2 e^{\frac{-t-t_{r1}}{\beta_2}} + B\alpha_3 e^{\frac{-t-t_{r2}}{\beta_3}} + C\alpha_4 e^{\frac{-t-t_{r3}}{\beta_4}} \tag{3.5}$$

where A, B and C are coefficients; t is the age of the structure in years; t_{r1}, t_{r2} and t_{r3} are the ages of the structure at the point of repair; $Y_{(t)}$ is the structural condition rating at age t and α and β are the regression parameters.

3.3.3 Artificial Intelligence (AI) Modelling

AI modelling is a relatively new area of research, but has been gaining significance in the field (Lee et al., 2015; Chen and Burrell, 2001). It is often considered a type of deterministic model, although with more complex relationships. A common issue with most modelling techniques is that large quantities of data are required, but are often not available. Frangopol et al. (2004) mentions that the concept of AI modelling is notable as it seeks to predict an assets condition based on the historical deterioration behaviour of other similar assets.

3.3.3.1 Case-Based Reasoning (CBR)

CBR is a technique designed to group similar assets based on factors (e.g. material type, maintenance, age, operational stress, etc.) and to generate missing historical records. The concept is that a similar asset, under similar conditions, will have a similar deterioration behaviour. The process begins with the target asset that requires condition prediction, all the assets in the database are potential stores of data. Then the "case retrieval" activity begins where each asset is analysed against similar assets based on the closest locational, operational and maintenance records. This stage uses a similarity function to calculate the suitability of the stored assets to the target asset, with the return value being between 0 and 1; with the closer to 1 being more suitable. Each factor is weighted depending on how suitable the stored asset property is with the target asset, the closer the situation, the more prominent the weighting. Depending on the results of the case retrieval, a weighting or modification factor can be added depending on expert judgement.

Morcous et al. (2002a,b) puts forth a model based on CBR. Their model employs the database of the Ministry of Transportation of Quebec (MTQ). The data was filtered to only assets that have three inspection

records or more, reducing the database to 240 concrete bridges with a total of 521 bridge spans. The database of bridges contained approximately 220 asset properties in three categories: administration data (e.g. location, jurisdiction), technical data (e.g. traffic, material) and descriptive data (e.g. structural system, geometry). From these attributes, 6 main attributes were chosen: total width, number of beams, beam spacing, construction date, inspection date and age of bridge. These attributes were used in the training stage of the process with the similarity function to ascertain their closeness to the target asset. During the data filtering process, the author noted that the inspection period was not regular, but had an average of 2.8 years with a standard deviation of 0.73 years. This technique would also, therefore, be able to cope with irregular inspection frequencies. Out of the 521 bridge spans in the dataset, 259 bridge spans were used in the validation of the model. They were chosen because they had the most number of sequential inspections. They were grouped, each with 30 cases. One set was used as a training set whilst the other was the testing group. The method that was used was to select the top 5 retrieved cases that had a similarity value greater than 0.75. The results revealed the accuracy of the CBR approach ranged from 78% in training (to retrieve suitable cases from the library) to 84% in testing (applying the adjusted weights in case adaptation). The paper concludes with a discussion about the advantages and disadvantages of the CBR technique. The advantages of CBR are that it 1) reduces the uncertainty and spread of the deterioration rates, 2) that CBR is not restricted to constant inspection periods and that 3) CBR interprets the deterioration behaviour between different bridge components. The disadvantages of CBR are that 1) the similarity function uses weights that are difficult to determine and subjective if derived from expert opinion and 2) the adaptation of the historical records to the target asset use engineering judgement which is subjective. However, the major disadvantage to CBR as an AI modelling technique is that it is meant to help predict

asset condition when there is a lack of data, however the process relies on a plentiful set of historical asset records to generate the information from. If the case library is inadequate or incomplete, then the predictive capability of the model is undermined.

3.3.3.2 Artificial Neural Networks (ANNs)

The use of ANNs in the Backward Prediction Model (BPM) generates incomplete historical condition ratings. The BPM uses a complex system to analyse the library of historical asset information; each asset is analysed for its specific asset and non-asset factors (e.g. maintenance policies, jurisdiction). The non-asset factors can directly or indirectly affect the condition of the asset. The principle of BPM is similar to CBR in the sense that the library of assets are used to predict the future condition of the target asset. Each neural node takes inputs from a database and determines the output of the neuron. Depending on the strength of respective relationships of inputs, the inputs are multiplied by weights. The stronger a relationship the more heavily weighted the inputs. Negative relationships can be used to inhibit an input to a neuron. The process of adjusting the weights to yield an optimal output is known as the training/leaning process. A simple example can be seen in Figure 3.1. The input nodes on the left connect to the neurons in the middle with weighted arcs. The neurons in the centre then feed their information to the output node on the right. The technique was first demonstrated for bridge deterioration modelling by Sobanjo (1997) who used a library of 50 superstructures. The data was split into two sets with 75% used to train the neural network and the rest to validate the model. The age of the asset was used as the training criterion with the condition rating being the output. The result validated ANN as a possible technique for bridge deterioration prediction modelling.

Lee et al. (2012) analysed the deterioration of bridges using a BPM approach. Using data from the Maryland Department of Transport (MDoT),

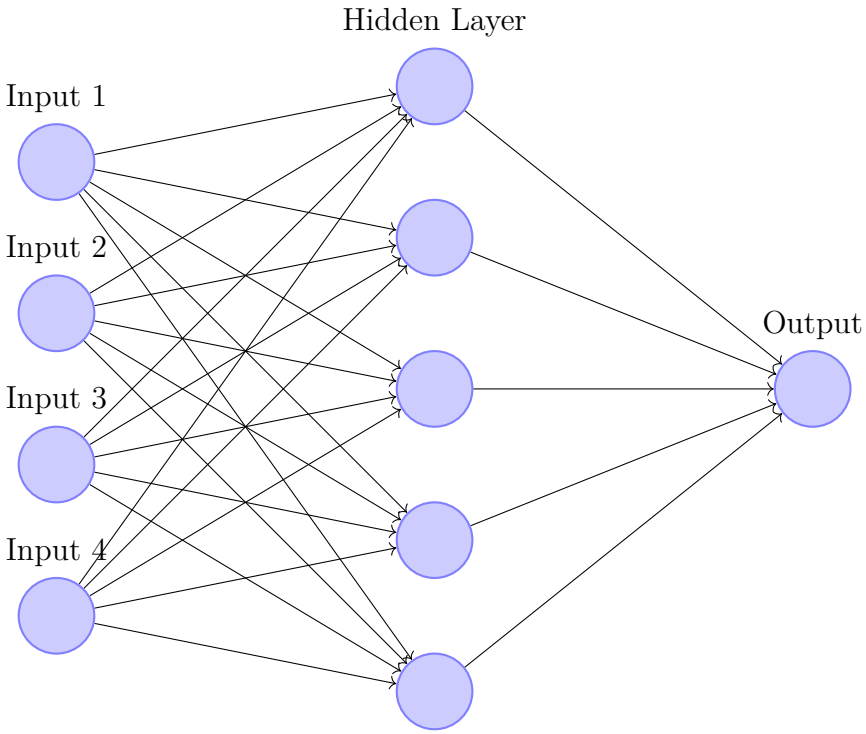


Figure 3.1: Example of how an ANN interconnects the inputs and output with neural nodes

USA. The author used 66 cases in the study to represent each bridge element. The output of the ANN was a condition score, CS, which represents the complete bridge condition. The author describes the validation process as taking a sample asset with historical data and temporarily removing this historic data. The library of assets are used to generate the historical data of the target asset. The generated data was compared to the actual historic data to hone the function for better accuracy.

Arditi and Tokdemir (1999) reports on the use of ANNs and BPMs. This paper did not study structural degradation, however the approach used ANNs to predict construction litigation. They use 12 case studies to train the ANN with a total database of 102 case studies. Their approach was to use 45 input properties to the neural network to predict the outcome, a for/against decision based on the case litigation. The decision making process could be likened to a bridge manager who must consider the asset

condition score before making a decision on maintenance. The authors used a computer program, "Brainmaker", which uses a BPM in a supervised learning algorithm. The authors detail the dangers of too many hidden nodes in the ANN. One scenario used 90 nodes which resulted in 8,640 connections within the ANN, making it difficult to check and complex to compute. That number of nodes was justified due to the noisiness of the data and that no clear patterns were emerging. By increasing the number of nodes, the network will be able to define the particular relationships with greater granularity, however too many nodes will jeopardise the reliability and robustness of the model. The paper concludes with the best tested scenario which yielded a BPM prediction rate of 83% for predicting the outcome of a case study decision.

Morcous et al. (2002b) summarised the use of ANNs and BPMs as being advantageous in the fact that it features an automated process of finding the optimal relationships of inputs. On the other hand, as the network tries to understand the relationship between the inputs, it exhibits the classic behaviour of deterministic models and therefore ignores the overwhelming notion from literature, which is that structural degradation is a stochastic process and this approach neglects that (Jiang and Sinha, 1989). Additionally, the supervised learning approach can be influenced by subjectivity in the weightings, which affects the quality of the future condition predictions. Finally, as the BPM becomes more sophisticated and the number of inputs grow, an extensive library of assets is required to maintain the quality of the network and understand the asset behaviour.

3.3.3.3 Deterministic Modelling Summary

In summary, deterministic models attempt to describe the relationship between two or more variables deterministically. The unique attribute of these models is that they ignore randomness which means that the results are exactly repeatable. Morcous et al. (2002b) argues that deterministic

models suffer from a number of drawbacks which make them unsuitable for predicting structural deterioration:

- structural degradation is inherently stochastic and this approach neglects that (Jiang and Sinha, 1989).
- the approach disregards interactions between elements.
- the approach often only predicts futures of assets with a "no maintenance" strategy because of the complexity of including the effects of maintenance (Sanders and Zhang, 1994).
- the models are difficult to update when new data is obtained.
- the prediction results in an average condition of many assets in the network regardless of the deterioration history of individual assets (Jiang and Sinha, 1989).

3.4 Stochastic Modelling Techniques

Many authors consider stochastic models to be superior to deterministic models for structural deterioration. Stochastic models use random variables and probabilistic distributions to predict the deterioration over time. Frangopol et al. (2004), amongst others, states that it would be better to model deterioration in terms of a time-dependent stochastic process. Morcous et al. (2010) reports from Ditlevsen (1984) that structural deterioration is a complex process and there is a considerable amount of uncertainty in the structures "micro-response" which means that stochastic models offer more realism and robustness beyond deterministic models. Frangopol et al. (2004) takes this further and says that Markov models are so widely used in the field of structural deterioration modelling that models are "assumed" to be Markov based. Not only should a structural model be able to consider deterioration over time, but also the changeable demands to the asset

over time. This includes, but is not limited to, changes to the assets usage profile, inspection regime and maintenance strategies.

3.4.1 Bayesian Belief Networks (BBNs)

Causal probabilistic networks, of which BBNs are a variant, have been created for infrastructure asset management for the last 3 decades (Casciati and Faravelli, 1992). BBNs consist of 1) a Directed Acyclic Graph (DAG), where each of the nodes represent random variables and the edges represent the causality between the variables and 2) a Conditional Probability Table (CPT) within each of the nodes to indicate which state the random variable is in. BBNs can be further evolved into Dynamic Bayesian Networks (DBNs) which are temporally linked BBNs which contain replicated connections for each time step or slice over the model period.

Rafiq et al. (2015) investigated the use of BBNs for bridge deterioration modelling. A BBN was created for each of the interconnections between the elements on the bridge asset. To enable the BBN to be used over time for deterioration modelling, it was evolved into a DBN. The authors state that there are 27 possible condition states for the elements of masonry arch bridges which they use as their example asset. To create a CPT for every condition state would be complex, so the authors create a simpler approach. The authors describe an existing method for calibrating the CPTs which uses simplifying constraints and a log-linear model (Celeux et al., 2006). A new approach is proposed which uses the existing industry standard Structure Condition Marking Index (SCMI) which is linear condition scale ranging from 0 to 100. The authors divide the SCMI range into three condition "states": Poor, Fair and Good. They use a Markov chain approach to calibrate the CPT primary for the three condition states, but also expand that to a five condition state model. The authors state that both the three-state and five-state models mimic the existing SCMI sys-

tem accurately. Overall, the paper shows that BBNs have a strong ability to model interconnections between the bridge elements, which is an advantage over other modelling approaches. However, accurate calibration of the CPTs seems highly complex, hence the need for simplifying constraints and the reliance on other modelling approaches. This limits the effectiveness of BBNs as a WLCC modelling approach for bridges.

3.4.2 Markov Models

Markovian models can be divided into two classes: the Markov Chain which is a discrete state space (and usually time) process and Markov Processes that are continuous. The two fundamental assumptions are: 1) that the current state relies only on the immediately preceding state and 2) the time for the process to move from one state to another follows an exponential distribution. A unique property of Markov models is known as "memoryless", this is because the next active state depends only on the current state and ignores all previous history:

$$P(X_{n+1} \mid X_0, \ldots, X_n) = P(X_{n+1} \mid X_n) \tag{3.6}$$

where X_n represents the current state and X_{n+1} represents the next state; $X_0 \ldots X_n$ are the states between 0 and n.

A Markov chain uses discrete time points $0, 1, 2 \ldots$, where p_{ij} is the probability of moving to state j from the current state, i. The matrix P with elements p_{ij} is known as the Transition Probability Matrix (TPM), the formulation of which is discussed in section 3.4.2.2.

A Markov process also considers discrete states, however it is a continuous-time process. This means that transitions behave differently from a Markov chain. The transitions are triggered after an exponential amount of time and move to state j from state i, where $i \neq j$. If the system is in state i, then the movement to state j happens with a rate q_{ij}. The exponential

transition time is controlled by parameter q_{ij}. The matrix Q with elements q_{ij} is known as the Transition Rate Matrix (TRM) or Intensity Matrix.

3.4.2.1 Markov Model Structure

The structure of Markov models consists of transitions and states. The status or condition of the asset is represented by states. There is a finite set of states the asset can reside in. The condition of the asset changes from state to state depending on the transition probabilities. Markov models are often shown as a directed graph. An example of a Markov directed graph can be seen in Figure 3.2. The nodes represent states, the labels on the edges represent the probability of moving from one state to another over a time interval. The direction of the edge represents the ability of the asset to move from one state to another, with an associated probability. Edges that point back into the same node symbolises an asset that has not changed state.

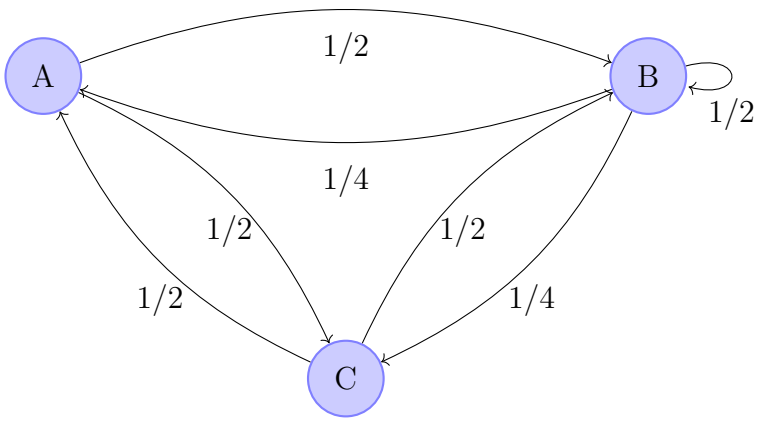


Figure 3.2: An example of a Markov directed graph

3.4.2.2 Markov Transition Probabilities

One can create a TPM to show all the transition probabilities between states in a single time interval. The TPM element P_{ij} is the probability of

moving to state j considering the asset was in state i at the start of the time interval. The TPM for Figure 3.2 can be seen in Equation 3.7.

$$[P] = \begin{bmatrix} P_{AA} & P_{AB} & P_{AC} \\ P_{BA} & P_{BB} & P_{BC} \\ P_{CA} & P_{CB} & P_{CC} \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{4} & \frac{1}{2} & \frac{1}{4} \\ \frac{1}{2} & \frac{1}{2} & 0 \end{bmatrix} \tag{3.7}$$

The probabilities of moving from one state to another after several time steps is $[P]^n$ where n is the number of time steps required. An example of this can be seen in Equation 3.8.

$$[P]^2 = \begin{bmatrix} P_{AA} & P_{AB} & P_{AC} \\ P_{BA} & P_{BB} & P_{BC} \\ P_{CA} & P_{CB} & P_{CC} \end{bmatrix} \begin{bmatrix} P_{AA} & P_{AB} & P_{AC} \\ P_{BA} & P_{BB} & P_{BC} \\ P_{CA} & P_{CB} & P_{CC} \end{bmatrix} = \begin{bmatrix} \frac{3}{8} & \frac{1}{2} & \frac{1}{8} \\ \frac{1}{4} & \frac{1}{2} & \frac{1}{4} \\ \frac{1}{8} & \frac{1}{2} & \frac{3}{8} \end{bmatrix} \tag{3.8}$$

Equation 3.8 shows the probability of moving from one state to another after two time steps for the example in Figure 3.2. If the asset starts in a known condition state, it is possible to multiply the TPM by an initial condition matrix to find the probabilities of staying in the initial state or moving to other states.

Markov chains are known as homogeneous or stationary if the transition probabilities are only dependant on the length of the separating time interval. If the next states transition probability is constant in time, given that the current state is also constant with time, then the TPM is constant. A time-homogeneous Markov chain is defined as:

$$P(X_{n+1} = j \mid X_n = i) = p_{ij} \tag{3.9}$$

where X_n represents the current state and X_{n+1} represents the next state; p_{ij} is the probability of moving to state j from the current state, i. If the

process is not stationary, it is said to be a dynamic process and known as a semi-Markov process. More can be read about semi-Markov processes in section 3.4.2.8.

3.4.2.3 Frequency Approach to Transition Probability Matrix (TPM)

The transition probabilities in asset models are often not known so a number of different approaches have been developed to deduce the probabilities (Ortiz-Garcia et al., 2006). The frequency approach is a simple, logical approach to generating the transition probabilities (Ng and Moses, 1996). This approach generates a p_{ij} value from the Maximum Likelihood Estimator (MLE) using:

$$p_{ij} = \frac{n_{ij}}{n_i} \tag{3.10}$$

where n_{ij} is the number of structures originally in state i which have moved to state j in the time period; n_i is the total number of structures in state i before the time period. This approach requires equally spaced observations of the condition index to function correctly.

3.4.2.4 Regression Approach to Transition Probability Matrix (TPM)

The MLE approach is only one way of calculating the transition probabilities in the TPM. Ng and Moses (1996) discusses an alternative approach known as the regression approach. The most common form of regression is known as the least-squares fitting approach. This approach fits a trend line within the data by finding the sum of the squares of the vertical distances from a function. The further the data points are from the line, the larger the sum of squares of their distances. The method is called least-squares as the trend line that best describes the data will have the least sum of squares of all those tested.

Ortiz-Garcia et al. (2006) describes three different methods of generating transition probabilities using the regression approach for a TPM. The author obtains the condition rating of the assets over time and fits an optimal trend line to the data from which they generate transitional probabilities for the TPM.

The first method is designed to be used in situations when all the historic condition data is available. The condition of asset j at time t is given by c_{jt}. The condition is scored from 0-100, with 100 being a new bridge. The equation, 3.11, is a minimisation function designed to give the least sum of squares:

$$Z = min \sum_{t} \sum_{j} (c_{jt} - \overline{y}(t))^2 \tag{3.11}$$

where Z is the objective function to be solved for; $\overline{y}(t)$ is the predicted average condition score of the assets. The equation considers the minimisation of both t and j as the variable c_{jt} relies on both. The minimisation is designed to reduce the sum of squares to optimise the line of best fit.

The second method builds upon the first equation (Equation 3.11) with a new parameter denoted as $y(t)$. The regression function minimises the difference between the average condition at time t and the regression equation. This should allow one function to describe the average condition over the whole lifetime of the asset. Again, the objective function, Z, is a minimisation function which is used to obtain the least squares difference between the regression curve and average asset condition to obtain the transitional probabilities for the TPM. The equation only considers the minimisation of t as it features in the variable $y(t)$:

$$Z = min \sum_{t} (y(t) - \overline{y}(t))^2 \tag{3.12}$$

Jiang and Sinha (1989) used a slight variation of this equation to esti-

mate their transitional probabilities:

$$Z = min \sum_{t=1}^{N} |y(t) - E(t, P)| \tag{3.13}$$

where N is the number of years in one time step (6 was found to be optimal (Jiang and Sinha, 1989)); P = the vector length of probabilities; $y(t)$ = the average condition rating at time t; $E(t, P)$ = the predicted average asset condition rating at time t.

The author attempts to use a "zoning" technique to obtain the transition probabilities in a TPM. The authors use this technique to avoid over or underestimating the asset condition which can occur if a homogeneous Markov model was used. One year transitional periods were used but then grouped into 6 years which was used to reduce computational time without significant change of results. Their equation uses the modulus of the difference between the average asset condition rating (from historical data) and the predicted average asset condition rating. The minimisation is designed to fit the trend line most closely to the historical data so accurate transitional probabilities can be calculated in the TPM. The reason modulus is used is to make all values positive which can also be attributed to the squared function in Equation 3.12 and 3.11.

The third method described by Ortiz-Garcia et al. (2006) groups the condition score of the assets over time. From this a distribution is generated which the transition probabilities can be calculated from. The minimisation function is designed to minimise the difference between the distribution observed from the grouped condition data and the generated distribution. From there the fitted distribution is used to calculate the transition probabilities for the TPM. The minimisation is given by:

$$Z = min \sum_{t} \sum_{i} (a_t(i) - a'_t(i))^2 \tag{3.14}$$

where $a_t(i)$ denotes the ith element of the distribution and $a'_t(i)$ denotes the ith element of the initial data distribution. The function is a minimisation function using both $a_t(i)$ and $a'_t(i)$ respectively. These are calculated from:

$$a_t = a_0[P]^t \tag{3.15}$$

where a_0 is the distribution of conditions initially; a_t is the distribution of conditions at time t and $[P]^t$ is the TPM matrix raised to the power of time, t, in years.

This method minimises the difference in the distributions obtained from the raw data (used in the first two methods). The fitted distribution is then used to generate transition probabilities in the TPM.

Chase and Gaspar (2000) used a similar method with the following equation to minimise the difference between $E_{i,j}$, the estimated condition state matrix, and $O_{i,j}$, the normalised observed condition state matrix:

$$Z = min \sum_{i}^{M} \sum_{j}^{N} (E_{i,j} - O_{i,j})^2 \tag{3.16}$$

Once $E_{i,j}$ is fitted, each row is used to determine the transitional probabilities in the TPM. The authors explain that, given a population of bridges, they can form a matrix of $N \cdot M$ where N corresponds to the number of bridges in each condition state and M is the maximum age of the population of bridges. If the transition period is selected as 1 year then the number of transitions equals the age of the bridge. This equation follows the same structure of being a minimisation equation between $E_{i,j}$, the estimated condition state, and $O_{i,j}$, the normalised observed condition state matrix.

3.4.2.5 Transition Rate Matrix

Moving from Markov chains to Markov processes, a TRM or Intensity Matrix can be created defining the rate of movement from one state to another. The structure follows the q_{ij} nomenclature and describes the rate of leaving state i and arriving in state j. With the TPM the sum of the matrix rows was 1, with the TRM the sum of the rows is 0. A typical TRM can be seen in Equation 3.17.

$$[Q] = \begin{bmatrix} -\lambda_0 & \lambda_0 & & & & \\ \mu_1 & -(\mu_1 + \lambda_1) & \lambda_1 & & & \\ & \mu_2 & -(\mu_2 + \lambda_2) & \lambda_2 & & \\ & & \mu_3 & -(\mu_3 + \lambda_3) & \lambda_3 & \\ & & & & \ddots & \end{bmatrix} \tag{3.17}$$

The TRM is useful for determining the most likely route the asset may take through the condition states which is useful for error checking. The transition rates can be compared and contrasted with expert judgement to detect any anomalies.

3.4.2.6 Existing Markov based Models

Markov based models have been used for bridge deterioration for 25 years. Jiang and Sinha (1989) were one of the first to study bridge deterioration with a Markov based model. They used a population of 5,700 bridges in Indiana, USA, from which 50 were randomly selected as samples. The methodology was proposed to generate the transition probabilities based on condition score data of bridges of different ages. The bridge conditions were scored by guidelines set out by the Federal Highway Administration (FHWA) from 0 to 9 with 9 being the rating of a new bridge. They noticed that as the bridge ages the deterioration rate also changes. The

authors demonstrated that Markov based approaches would be useful in this stochastic situation. The paper has been widely cited as pioneering the technique, however there was no application on bridge condition data.

Cesare et al. (1992) developed the technique further by incorporating a repair policy into the model. The study used 850 bridges in New York state totalling over 2,000 spans. The Markov chain model was designed with 7 states ranging from 1, potentially hazardous, to 7, new condition. Their approach splits the asset into major components e.g. superstructure, deck and piers. The model assumes that deterioration of each element is independent of all other bridge elements. The repair policy is implemented with a repair matrix that improves the condition by either 10% or 20% of the bridge condition scores in condition state 3 or less. There is little clarification about the repair policies but the authors claim to be able to predict the evolution of the average condition state of a set of bridges and the condition for a specific bridge. This approach was used by the American Association of State Highway and Transportation (AASHTO) to create Pontis which serves as the most widespread BMS. It is used to manage over 500,000 bridges in 45 US states (Sobanjo and Thompson, 2011).

Scherer and Glagola (1994) attempted to apply the Markov approach to real-world data from 13,000 bridges in Virginia. The authors use the same 7 states as in Cesare et al. (1992). However the authors use the condition of the whole bridge rather than bridge components. The author describe that the Markov chain approach creates S^n states where S is the number of states and n is the number of assets in the study. This would have created $7^{13,000}$ states which contemporary computers would have struggled to simulate. To tackle this issue the author creates a number of classes based on: road system, climate, traffic loading, bridge spans, bridge age and bridge type. The total number of classes is 216 and a typical bridge example was chosen for each class. This reduces the number of states to

7^{216}. The issue with using this approach is when a bridge moves between groups over its lifetime due to deterioration.

Morcous (2006) studied the Quebec bridge population, totalling 9,678 structures, including bridges of different types and culverts. Overall the data included 500,924 element inspections from 1997 to 2000. The performance indicator ranged from 0-100 with a higher number indicating a better condition. All inspection changes that indicated an increase in condition were striped out to eliminate the effects of maintenance or inspector variance. The paper lays out some assumptions: firstly, bridge inspections are assumed to be carried out at a pre-determined fixed interval. Secondly, future bridge condition depends only on present condition, ignoring historical conditions, highlighting the "memoryless" Markov property. Morcous (2006) states that these assumptions affect the reliability of the predictions and that the assumptions were designed to reduce the computational complexity and streamline the decision-making operation. The paper analyses the inspection interval to compute a normally-distributed inspection interval with a mean just over 2 years. The paper calculated the TPM using the frequency approach (Ng and Moses, 1996). This paper incorporates a different approach using Bayes' rule which is used to adjust the TPM for the variance in inspection frequency. This is then compared to the before and after effects of Bayes' rule. The paper closes with a figure of 22% for the improvement possible in estimating the service life of the bridge decks, the most critical component, with the inclusion of Bayes' rule in the adjustment of the TPM.

3.4.2.7 Augmented Markov based Models

Robelin and Madanat (2007) developed upon the traditional Markov model TPM approach by introducing three new variables (β,m,τ) which were chosen for their accuracy and simplicity to reduce uncertainty in the model. β represents the condition of the deck in the form of a reliability index; m

is an integer used to indicate the last action on the bridge: maintenance, renewal or null if the component was recently replaced; τ represents the time since the last action, m. The augmented Markov approach tries to overcome the "memoryless" attribute of Markov-based models. The advantage is that the succeeding state takes into account all of its historical data rather than just the current state. The author compares Markov models and augmented Markov models, commenting that in a standard Markov model, if the current condition of the asset is 5, then a particular maintenance policy is attached to that. However with augmented Markov models, the additional variables describe the previous maintenance action and how recent the action was and therefore it is possible to make a more informed decision about intervention actions. If the asset is in state 5, but it is known that a component replacement occurred 3 years ago, there may be a different policy action than if the replacement was 7 years ago, for instance. Robelin and Madanat (2007) generates information about when maintenance will be required rather than comparing average condition over the assets lifetime. The author combines Ng and Moses (1996) approach with the augmented Markov approach to yield Equation 3.18.

$$P(\beta_{t+1}, m_{t+1}, \tau_{t+1} | \beta_t, m_t, \tau_t) = \frac{N^{transitions}_{(\beta_t, m_t, \tau_t),(\beta_{t+1}, m_{t+1}, \tau_{t+1})}}{N^{total}_{(\beta_t, m_t, \tau_t)}} \tag{3.18}$$

where $N^{transitions}_{(\beta_t, m_t, \tau_t),(\beta_{t+1}, m_{t+1}, \tau_{t+1})}$ is the number of times a component moves from state (β_t, m_t, τ_t) to state $(\beta_{t+1}, m_{t+1}, \tau_{t+1})$ in one time interval; $N^{total}_{(\beta_t, m_t, \tau_t)}$ is the total number of components in state (β_t, m_t, τ_t).This study introduced some novel additions and improvements to the traditional Markov approach, however the additional complexity in calibrating such a model negates the lightweight-ness of a Markov model.

As mentioned by Niroshan et al. (2015), one of the most recognised Markov limitations for bridge deterioration modelling is that the approach

relies on the Exponential distribution which is often not suitable for structural deterioration. To overcome this, the authors augment the traditional Markov approach with Weibull-based TPM parameters. There is evidence to suggest that the Weibull distribution is superior for modelling deterioration of infrastructure assets (DeLisle et al., 2004; Agrawal et al., 2010). The authors mention that they chose to use a homogeneous time Markov Chain approach as the parameters calculated for the model would be of direct interest to bridge managers whereas the time-dependant functions used in a non-homogeneous semi-Markov approach would be less so. In a previous study (Niroshan et al., 2014), the authors compare different fitting approaches of the TPM using the a regression optimisation approach, a Bayesian Maximum Likelihood optimisation method and a new proposed method using a Metropolis–Hastings algorithm optimisation approach which uses Markov Chain Monte Carlo (MC) simulations to fit the parameters of the TPM to the historic data. The study found that the proposed solution, using Markov Chain MC simulations was the best performer and also had the lowest Chi-Squared result (the test to which the quality of the fit was measured). The later study, Niroshan et al. (2015), then used the same fitting approach but used a Weibull distribution for each of the TPM parameters. The resulting model was able to predict the percentage of bridge elements in each conditions state over the simulation time period. The study concludes that the Markov model augmented with Weibull TPM parameters was suitable for modelling network level deterioration and even calculate the uncertainly in the model parameters. The study puts forward an interesting development on the traditional Markov model with the use of a Modified Weibull approach. However, the study focused on network level deterioration modelling only and there was no discussion if the technique was flexible enough to be used in greater granularity (i.e. on asset or sub-asset level). Additionally, interventions were not discussed, both of these factors would be critical aspects of a model

designed for use within a BMS. By introducing Weibull distributions into the TPM, the approach requires the use of MC simulations which removes one of the main advantages of the traditional Markov approach, its ability to be analytically solved with minimal computation.

Overall, augmented Markov approaches try to overcome some of the limitations of the traditional Markov model, but this can introduce other limitations or sources of uncertainty.

3.4.2.8 Semi-Markov based Models

Semi-Markov models conform to the first Markovian rule, that the current state relies only on the immediately preceding state, but not the second one, that the time for the process to move from one state to another follows an exponential distribution. The reason for this is to try to overcome some of the limitations of Markov models, for instance, modelling inspections that are rarely carried out at regimental frequencies and their intervals can vary (Yang et al., 2009).

Ng and Moses (1998) are widely cited as producing one of the first semi-Markov bridge deterioration models. The authors state that the traditional Markov Chain approach uses underlying assumptions which may not be suitable for bridge deterioration modelling. For example, the "memoryless" property of a Markov Chain means that the probability of a bridge element to move from its current condition state to the next does not depend on how long it has resided in the current state. The authors argue that the requirement for an exponential holding time with the traditional Markov Chain means that a semi-Markov approach may be more suitable. The authors define the movement from one state to another using the Weibull distribution which is commonly used to represent a lifetime distribution in deterioration modelling. They apply their model to the National Bridge Inventory of Indiana which includes data for 1,000 bridge assets. The element condition scale varies from state 1, for those in the best con-

dition, to state 7, for those in the worst condition. The authors compare the performance of the models predictions over 80 years to a traditional Markov Chain model from Jiang and Sinha (1989). The results show that semi-Markov models are better in the long-term prediction of asset deterioration which the authors attribute to the probabilistic distributions which lie underneath each of the models.

Yang et al. (2009) produced one of the more recent notable semi-Markov bridge deterioration models. The paper focuses on medium and short span concrete bridges in Hong Kong. Just over 50 bridges condition data was used to validate the semi-Markov model. The author selected the sample bridges if they contained condition data from 3 consecutive inspections. The author establishes a condition rating system which is based on the maintenance actions required to rehabilitate the bridge. They claim that this type of condition rating system is more appropriate for bridges with periodic inspections and therefore more suitable for the semi-Markov approach. The rating system is more explanative than other papers as it allows for a clear understanding that being in condition state 3, for example, means corrective maintenance would be required. The results of the paper suggest that semi-Markov models would be suitable for bridge elements that are inspected non-periodically and those which are inspected periodically satisfy the Markovian properties (given in Section 3.4.2). The study uses the approach to overcome some of the traditional issues that have plagued Markov-based approaches, however there was little verification with real-world data with this study.

Although semi-Markov models allow for the models to be calibrated with distributions that more closely fit the deterioration behaviour of structures, the disadvantage of this method is that due to the increased complexity of the TPM, the semi-Markov model is often simulated, using a MC approach, which means that the model loses the ability to be easily and quickly mathematically analysed i.e. one of the major advantages of

the traditional Markov Chain approach is no longer available using this method. Additionally, when trying to consider a varying number of elements on a bridge asset, a scenario which would be commonplace for a model within a BMS, the model will still experience the state-based explosion which is one of the major drawbacks of all Markov models. Overall, the semi-Markov approach seems to be able to model bridge deterioration in a way which is more true-to-life, but in doing do so loses one of the main advantages of the traditional Markov Chain approach and is still exposed to one of the major weaknesses which affects all Markov approaches.

3.4.2.9 Markov Limitations

The models that have been discussed are Markov based models. Markov models form the basis for the prediction module found in many BMS systems. They have had unparalleled adoption in the field of infrastructure facilities. Morcous (2006) makes it clear that the Markov approach is the most commonly used of all the stochastic models for predicting performance in bridges, highways, sewerage and water distribution. That is not to say that Markov models are without limitation. Additionally, some of the techniques used to simplify Markov model computation are not directly Markovian limitations, but are limitations to using the Markov approach in structural deterioration modelling. Some of those limitations include:

- Transition probabilities in the TPM are difficult to accurately calculate and can often require manipulation by expert judgement (Frangopol et al., 2004).
- Often inspection data where the condition has increased is disregarded due to difficulty in reliably ascertaining which assets were repaired and what repair action was applied (Robelin and Madanat, 2007; Morcous et al., 2002b).

- The condition states are defined as discrete states but often there will be borderline candidates and critical elements which require expert judgement for correct classification, which can be subjective. Frangopol et al. (2004) argues that a more detailed, continuous, measurement criterion would be superior.

- The Markov modelling approach suffers from a rapid expansion of states when interactions between elements are considered. The number of model states follows S^n where S is the number of states and n is the number of elements.

- In the context of bridge deterioration models, the "memoryless" property of a Markov Chain means that the evolution of the next condition state is not dependant on the time the element has resided in the current condition state, which may not be appropriate Ng and Moses (1998).

Although there are augmentations to the traditional Markov approach, including the semi-Markov model, to avoid some of the limitations listed above, often the technique results in other limitations or complications (see Sections 3.4.2.7 and 3.4.2.8).

3.4.3 Petri-Net (PN) Models

PNs were developed by Petri (1962). They have had increasing application in transportation, manufacturing and business for modelling dynamic, distributed systems (British Standards Institution, 2012). The traditional methods (e.g. fault tree, reliability block diagrams) are unable to handle concurrent multi-state systems, which PNs can do. Additionally, PNs can be monitored to reveal when systems move from state to state to aggregate statistics about component condition, failures and inspections (British Standards Institution, 2004).

3.4.3.1 Petri-Net (PN) Structure

PNs are directed bipartite graphs. They are built with two types of nodes: places and transitions. The places are representative of a system state (e.g. new, corroded, requires inspection). Transitions are used to create a change of state (e.g. from new to slightly corroded). Places may contain tokens, the position of the token(s) dictates which state(s) the system is in. The arcs are graphical representations of relationships between places and transitions. No two places or transitions can be directly connected with an arc/edge (Reisig, 2013). These components can be seen in Figure 3.3.

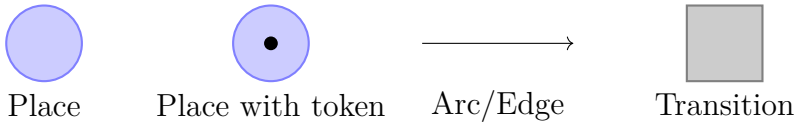
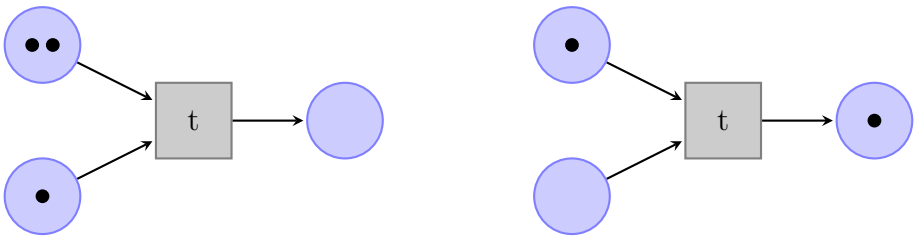


Figure 3.3: Components of a Petri-Net

3.4.3.2 Simple Petri-Net (PN)

The role of the transition is to absorb tokens from the input places and then to generate tokens in the output places. Thus, it requires a token in each of its input places to fire. In the example seen in Figure 3.4, there are two input places, both occupied by tokens. The transition has a firing delay of t; the initial marking of the PN can be seen in Figure 3.4a and after t in Figure 3.4b. When the transition fires a token from each input place is removed and a token is generated in the output place. In 3.4b, the transition is no longer enabled because there is no token in the bottom input place; therefore, the transition can no longer fire.

PNs can become more complex with multiplicities, inhibitor arcs and conflicts (Reisig, 2013). A multiplicity is shown with a value above the arc (as seen in Figure 3.5a). This value represents the number of tokens required to activate the transition. For instance, an arc with a multiplicity of three means that the transition cannot fire until the input place has

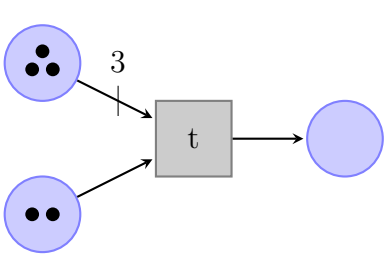


(a) Initial PN marking (b) PN marking after transition fires

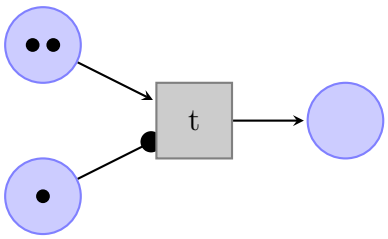
Figure 3.4: Simple example of a PN before the transition fires (a) and after the transition fires (b)

three or more tokens. No value indicates defaults to a multiplicity of one. An inhibitor arc is a type of blocking component where the presence of a token can disable the transition it is directed to. The inhibitor arc in Figure 3.5b has a token which means that the transition is being inhibited. Inhibitor arcs may be used in conjunction with multiplicity. For instance, if a transition should be disabled after four tokens are in the input place that inhibits it, this may be achieved with an inhibitor arc with a multiplicity of four, as seen in Figure 3.5c. Conflicts occur when two transitions share an input place and try to remove the same token at the same time. They are a PN modelling problem and something that should be avoided as they can cause erroneous simulation results (Schneeweiss, 2004). An example of a conflict can be seen in 3.5d.

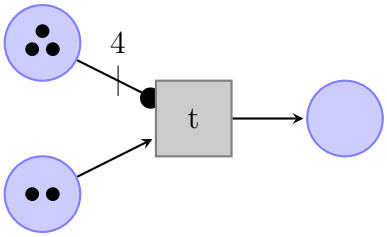
The stochastic nature of PNs comes from using probabilistic transitions. These transitions have the ability to be calibrated with any statistical distribution. For example, when creating a PN for use as the predictive base for a BMS, the probabilistic transitions could be embedded in the deterioration module, each calibrated with the specific statistical distribution which best describes the deterioration profile of the element. Probabilistic transitions are a feature which need to be simulated to output the system events and gain an understanding of the overall model behaviour. This is what renders PNs suitable for modelling.



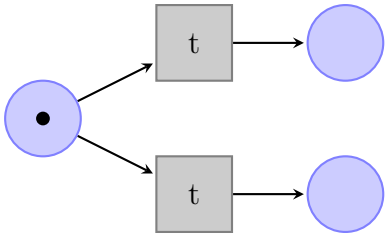
(a) PN example with multiplicity



(b) PN example with an inhibitor arc



(c) PN example with an inhibitor arc with multiplicity



(d) PN example with a token conflict

Figure 3.5: Examples of PN complexities

3.4.3.3 Coloured Petri-Net (CPN)

CPNs are an extension to simple PNs, previously discussed. They were developed by Jensen (1997) as the amalgamation of simple PNs and programming languages. British Standards Institution (2004) discusses the advantage of CPNs as a way of avoiding the exponential increase in number of states with the number of elements.

In simple PNs, the tokens are anonymous and indistinguishable, their importance comes from their presence/absence in the place. However with CPNs, there is an additional constraint: transitions can only be activated if all the input places have the correct number of tokens and the tokens must match the transition criteria, known as the "guard". An example of this in bridge modelling may be for a transition that operates on certain types of elements but not others e.g. bearing elements but not parapets. The transition would use the tuple information to determine if the token is suitable or not. The phrase "coloured" in CPNs does not necessarily mean that each token has its own colour; but only tries to clarify that now

tokens can be of different types with different data sets and characteristics. The data held within the token is known as the token "tuples". The tuples within the token could be modified by the transition, for instance if one of the pieces of information in the token was the age of the asset, that number could increase within the tuple when the transition fires and the asset ages.

The transitions become more sophisticated in CPNs as they do not simply consume and produce tokens at the allocated time, but they now perform functions on the data within the token itself. This affords CPNs a great deal of flexibility beyond simple PNs. A basic example of a CPN can be seen in Figure 3.6. The transition has two input places, each containing a token. The transition has a guard to satisfy which is that the input tokens both have to have integers larger than one. The token in the top place contains two pieces of information: an integer number and a string. The token in the bottom place only contains an integer number. The integer is bound to w and the string to s. The guard is satisfied, so upon firing, the transition consumes the input tokens and generates a token in the output place. This output token contains an integer and a string. The integer is the product of the two input token integers. The string remains unmodified in this example. The binding of the tuples, the satisfying of the transition and the subsequent modification of the tuple information is known as occurrence. This functionality enables a huge variety of features to be incorporated into PNs which affords it a high level of flexibility (Le and Andrews, 2016).

3.4.3.4 Current Petri-Net (PN) based Models

PNs are not as common as other conventional modelling techniques. Recent work demonstrated that PNs are appropriate for deterioration modelling (Andrews, 2013). The approach used four states to describe the asset deterioration process: new, degraded needing maintenance, degraded needing speed restrictions and degraded needing line closure. The model was de-

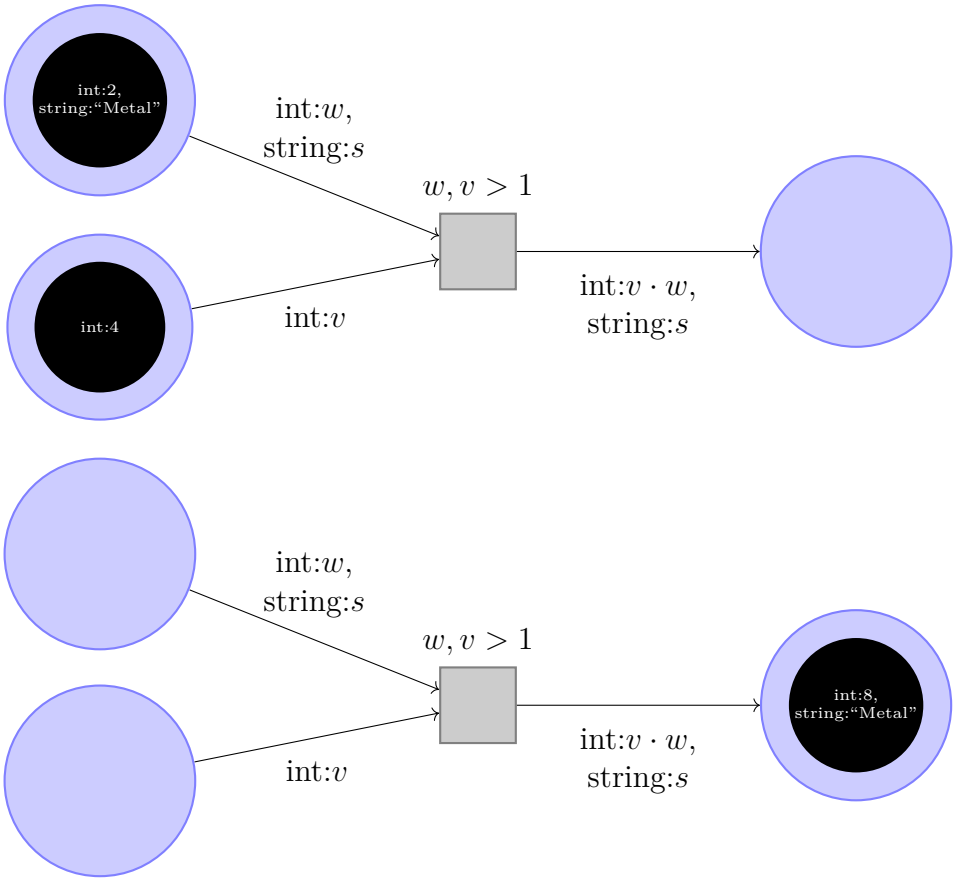


Figure 3.6: Simple example of a CPN before the transition fires (a) and after the transition fires (b)

signed for track deterioration rather than structural deterioration, however the author mentions that the PN modelling technique has a great deal of flexibility and the PN model presented in the paper is significantly more developed than others found in literature.

Rama and Andrews (2013b) used a number of simple PN subnets to model the railway infrastructure in a hierarchical, modular structure. A number of different sub-net modules were created for component deterioration, maintenance, inspection and renewal. A modelling framework was presented where the hierarchy was laid out. At the top level the whole railway is subjected to track, rail and geometry inspections. Then, at the lower levels, depending on that particular 1/8th of a mile section, sleepers,

fastenings and ballast are modelled. Each of the sub-nets connects to one another to create an asset life-cycle PN. For each section of track, the appropriate sub-net modules are amalgamated to model larger sections of the track. The authors mention that having a library of PNs specific to individual assets could be beneficial to generating a detailed, realistic model of the whole system.

Le and Andrews (2014, 2015) created a bridge model using a PN approach. A number of PN sub-nets were generated for the components that make up the bridge (e.g. deck, girders and abutments). Each component was detailed with deterioration, inspection and maintenance processes. For each bridge asset the elements are considered and the corresponding sub-PNs chosen to create a complete bridge model. The state descriptions in this model were not related to deterioration, but the maintenance action required for rehabilitation, similar to Yang et al. (2009). This model uses CPNs to track different individual bridge elements within the same sub-net. The advantage of CPNs here is that coloured tokens within a sub-net could hold tuple information. This can be used to obtain, for example, the number of maintenance occurrences before element replacement. The model inputs are deterioration characteristics for different bridge components and the maintenance/renewal strategy parameters. The authors use MC sampling for all stochastic transitions. A simulation duration of 60 years was used and the results converged after roughly 200 simulations; this took under 10 minutes to perform.

3.4.3.5 Petri-Net (PN) Advantages and Disadvantages

The advantages of PN models are as follows:

- PN models can be used to model many components of the same type without the state explosion that is seen with Markov models. Tokens need to be added with additional components as oppose to many more

states (British Standards Institution, 2004; Le and Andrews, 2014). In short, a common model can be used for girders and columns, for instance, each with different maintenance strategies and deterioration profiles dependant on the colour of the token.

- PNs allow the modeller to use the statistical distribution that is most suitable to the application. For a sub-net library of components, different distributions may be called depending on material deterioration, inspection intervals and resource allocation. The Markov approach is limited to exponential distributions.

- The graphical nature of the modelling approach (Remenyte-Prescott and Andrews, 2011) can be beneficial to the understanding of the PN. The PN modeller can visualise the tokens moving through the net which is a useful diagnostics and troubleshooting tool (Salimifard and Wright, 2001; British Standards Institution, 2012).

- The simplicity of the modelling approach affords it great flexibility. The transition information, token information, arc conditions, etc. can all be changed without changing the structure of the PN (Andrews, 2013). For instance, adding an additional token to a PN can be as simple as modifying a value. Unlike Markov, the inspection, deterioration and maintenance can be modelled in a single common framework.

The disadvantages of PN models are as follows:

- There are few software packages that are designed to model stochastic CPNs. One of the most popular tools is known as CPNTools, however there are a number of drawbacks for simulating asset management CPNs models including a lack of global timing, simulation flexibility and custom outputs.

- Due to the comparative newness of the modelling approach, not all terminology has been standardised yet and so understanding the features of a PN model in some literature can be difficult.
- In the context of bridge modelling, the PN approach will inevitably require probabilistic transitions which means that there is no analytical solution like that of the traditional Markov chain and therefore MC simulations are required.

3.4.3.6 Suitability for Bridge Management Systems (BMSs)

The predictive capability of a typical BMS can be divided into a number of modules: deterioration, intervention and optimal intervention strategies (Mirzaei et al., 2014). A PN based approach offers direct advantages in some of the modules, but not all. For example, in the deterioration module, the ability to have custom statistical distributions fitted to the specific deterioration profiles of the elements offers an advantage. Similarly, the ability to model assets with different numbers of elements without a state based explosion, as would be expected with a Markov based approach, is beneficial. However, with the intervention module, which predicts future work volumes, there would be no direct advantage simply from using a PN based approach. On the other hand, because the deterioration module can be calibrated more accurately to the specific deterioration profiles of the elements, there is an inherent advantage within the intervention module as the future work volumes can be predicted more accurately. Therefore, there is an overall benefit to employing a PN based approach for the predictive capability of a BMS.

In terms of stochastic model simulations, the traditional Markov model is computationally inexpensive compared to a probabilistic PN model which requires Monte Carlo simulations. However, considering computing power

is becoming much more plentiful (Nordhaus, 2007), the computational advantage of simulating a Markov model is diminishing over time.

3.5 Summary of Modelling Techniques

This chapter introduces a number of techniques available for modelling structural condition. A number of literature sources champion the probabilistic model over mechanistic and deterministic models for modelling management of structures. The chapter discusses the established Markov approach which has been used very widely and is very popular in the field of structures asset management. Notable models include Yang et al. (2009), who defined a more clear asset condition definition based on the maintenance actions required for rehabilitation, and Cesare et al. (1992) who tried to incorporate a repair matrix into the Markov model. The PN approach was then discussed which is more suitable for the prediction of structural deterioration due to the flexibility and simplicity of the model. Notable PN models include the framework laid out by Remenyte-Prescott and Andrews (2011) which uses a number of sub-nets and a master PN to form the model. Le and Andrews (2015) produced a PN-based model that focused on individual component sub-PNs which is more suitable to model structural condition.

Overall, there is a strong case that structural deterioration is a stochastic process and therefore a probabilistic method is preferred. Due to the numerous Markov limitations, explained in section 3.4.3.5, there is a suitable draw to using PNs to model structures asset management. Overall, it seems the advantages of PN for use as the predictive base for a BMS outweighs the disadvantages. Furthermore, the main disadvantage, the requirement for Monte Carlo simulations, is becoming less of a burden.

Chapter 4

Railway Bridge Petri-Net (PN) Model

The model which has been developed uses a bottom-up approach rather than a top-down approach. To that effect, the model is asset and sub-asset level rather than at the network level it is therefore, positioned in line with other Tier 3 approaches. The model represents an asset with the Petri-Net (PN) tokens representing elements of the asset. To model a complete bridge, each element of the bridge would be represented by a token in the model. The model is primarily condition based as this is currently the main driver of the decision making processes since it is often the only available information for large bridge stocks. The following sections detail the model structure including the modules, the calibration of the modules including the data source for the model, and finally some sample model outputs.

The motivation for choosing PNs over other modelling approaches is derived from the behaviour of bridge assets and the suitability of PNs for modelling them. PNs have the following advantages which make them particularly well suited to modelling bridge assets: 1) they allow a common framework model which allows for modelling interaction between elements,

2) they offer a flexible framework which allows the modification of the inspection and maintenance decisions, actions and policies both between infrastructure management organisations and over time, 3) they allow a greater range of statistical distributions which allows the possibility for using lifetime distributions which have become popular for modelling such assets (Niroshan et al., 2015) and finally, 4) they have an implicit variability with the use of stochastic transitions for the deterioration which many authors mention is an important attribute for capturing structural deterioration (Jiang and Sinha, 1989; Frangopol et al., 2004).

4.1 Modules of the Railway Bridge Model

The railway bridge model is designed to replicate the processes and procedures used by Network Rail (NR) with regards to bridges. However, the approach followed by NR is relatively common in the industry and the model developed can be adapted to other asset groups with minor changes. NR use a hierarchy of elements to split the bridge into its components. The hierarchy is used to aid with decision making, for instance, maintenance is decided upon at the Minor element level, however inspections are done at the Sub-Minor Element level. It seems no decisions are made at the Major Element level.

The PN bridge model which has been developed uses a number of Coloured Petri-Net (CPN) features, but is referred to as a PN model for simplicity. The CPN features are used in two ways:

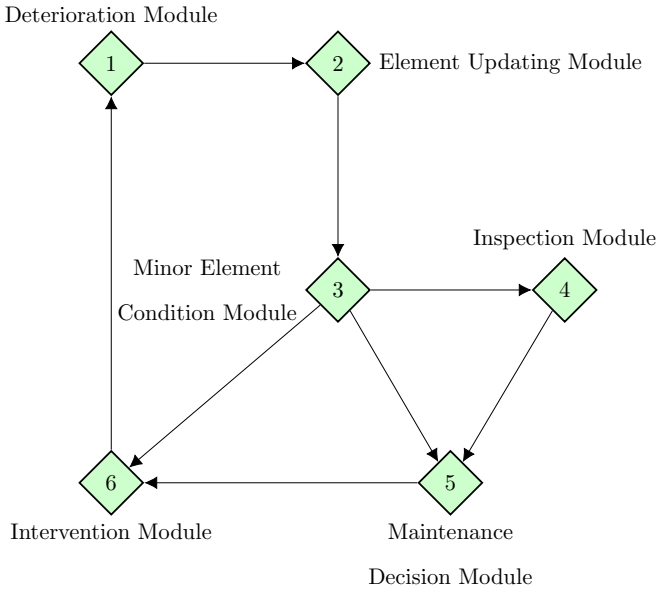
1. Each token contains tuple information about the element i.e. each token represents an element of the bridge and contains all the relevant information about that element within the token e.g:
    - Element type
    - Material

- Location

2. There are advanced transition functions built into the model which can aid in modelling complex decision-making processes without making the resulting model unduly complex e.g:

    - Probabilistic outcomes
    - Condition dependant delays
    - Condition transposing

The PN bridge model comprises of a number of "modules": the Deterioration Module, Element Updating Module, Minor Element Condition Module, Inspection Module, Maintenance Decision Module and Intervention Module. They each use different approaches and so each module is explained individually. Figure 4.1 gives a brief overview of the modules and how they link together to form the PN bridge model. Each module is its own PN and they link together into a master PN to form the generic bridge model. The Deterioration Module contains the sub-minor element tokens and controls their deterioration profile with a set of probabilistic transitions calibrated from historic data. The Element Updating Module analyses the condition of the Sub-Minor elements in the Deterioration Module and updates the Minor Element's condition of which they are a part. The Inspection module is calibrated with the industry standard policies for inspection which is linked to the element condition. Upon inspection, the Maintenance Decision Module is activated and the intervention choices selected for each element, based on industry standard guidelines. Finally, the Intervention module carries out the condition uplift on the appropriate elements. This module links back to the deterioration module. The full model can be seen in Figure 4.2.



1) This module controls the rate of deterioration of sub-minor element conditions. This module has been calibrated with historical data.	2) This module analyses sub-minor element conditions and then updates minor element conditions in the next module.	3) This module contains the minor element conditions and the thresholds for inspection and maintenance.
4) This module analyses the minor element conditions and determines the appropriate inspection interval.	5) This module decides upon the appropriate maintenance action depending on the minor element condition after an inspection.	6) This module performs rehabilitation on the elements. It also contains advanced decision making capabilities.

Figure 4.1: Diagram depicting the layout and a brief explanation of each of the modules that comprise the PN bridge model. The diamond-shaped nodes represent PN modules and are not part of the PN notation.

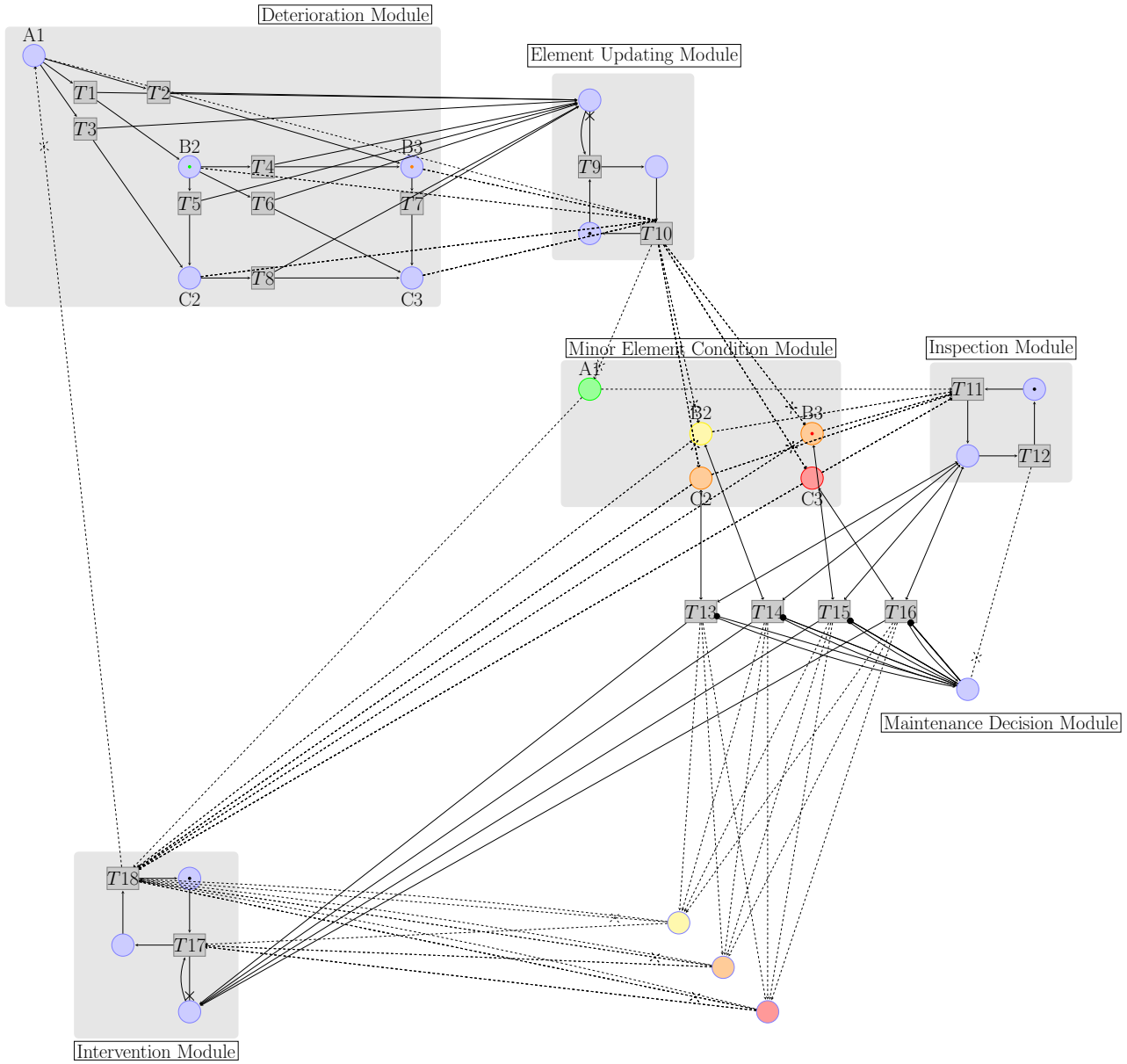


Figure 4.2: A simplified version of the full railway bridge asset management PN model. For illustration, only states $A1$ to $C3$ are shown, however, there are 31 states in total ranging from $A1$ to $G6$.

Figure 4.3 gives an example of events over time of a simplified bridge model framework. Consider a bridge element with a starting condition of $A1$. This condition, according to current policy, requires an inspection every 12 years (see Table 4.6). Transition parameters are calculated, based on historic data, for the possible movement (i.e. to condition states $B2$, $B3$ and $C2$). The possible movements between condition states can be seen in Figure 4.4. Monte Carlo (MC) samples are utilised to generate times using the transition parameters. Each transition is defined with its own parameter and MC sample. The transition with the probabilistically defined shortest time is selected. This transition fires at $t = 5$ which moves the system state from t_1 to t_2. At this point, the transition times are generated for the possible movement to condition states ($B3$, $C2$ and $C3$). Again, the shortest transition time is chosen and the element deteriorates to condition $B3$ at $t = 10$. Transition times are generated for the possible movement to condition states ($B4$, $C3$ and $C4$). However, at $t = 12$, the scheduled inspection takes place. This reveals the condition of the element to the bridge managers. According to current policy, an element in condition $B3$ would be eligible for a Minor Intervention (see Table 4.7). The inspection takes place at $t = 12$, however there is an associated delay to carry out the intervention whilst bridge possessions are scheduled and materials ordered. The intervention is carried out at $t = 13$ which, in this example, improves the condition of the element to the $A1$ condition. Another inspection is scheduled in a further 12 years. The deterioration starts again with the transition times from condition $A1$ to condition states $B2$, $B3$ and $C2$ generated.

4.1.1 Deterioration Module

NR inspect each Sub-Minor element of each bridge and give it a Severity Extent Rating (SevEx) rating according to its condition. The Deterioration

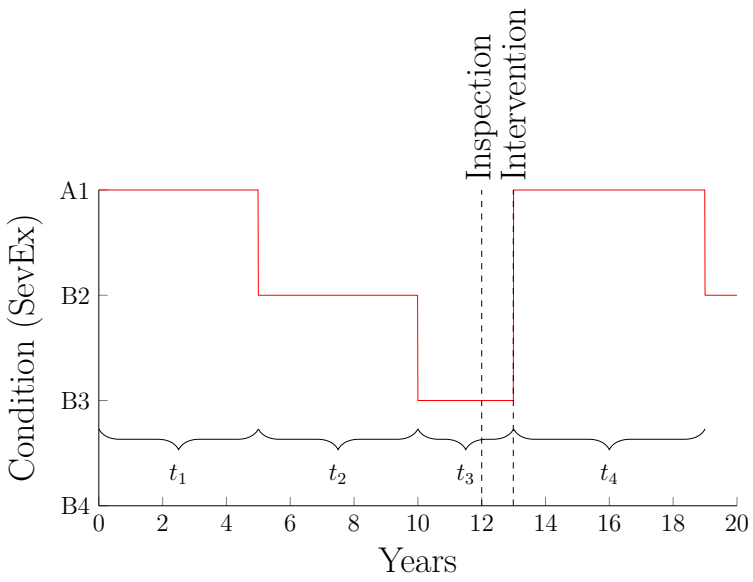


Figure 4.3: An example of a single bridge element. The effects of the deterioration, inspection and intervention modules are demonstrated.

Module replicates this system of conditions. The reason for this is that: 1) it allows for efficient transposing from the historical conditions database 2) it allows for the results of the PN model simulation to be exactly comparable to the system already used by NR 3) each SevEx condition has a well defined definition and finally, 4) by keeping the same data as the original format, no conversion is required where there is a loss of precision typically. The module replicates the SevEx condition ratings which go from A1 (perfect condition) to G6 (permanent structural damage). The full range of SevEx ratings and movements between the condition ratings can be seen in Figure 4.4.

A number of studies have investigated the failure modes of bridges (Wardhana and Hadipriono, 2003; Richardson et al., 1993; Priestley et al., 1996), the vast majority of the failure is due to extended manifested deterioration, however there are other more dramatic failure modes, due to bridge strike, scour and earthquake activity, for example. These latent deterioration processes lend themselves to being modelled by particular modelling approaches including fault and event trees (Sianipar and Adams, 1997;

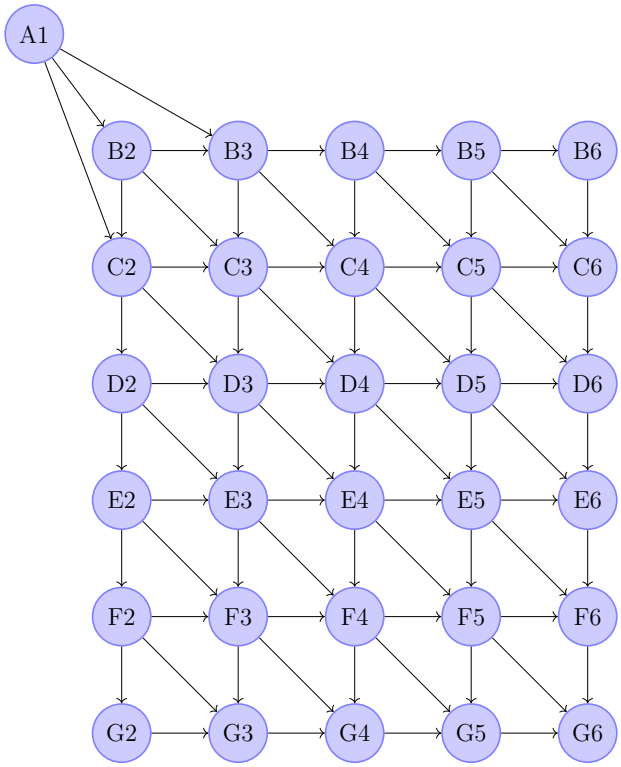


Figure 4.4: Condition states and their allowed progression; each of the states are connected to its neighbouring states, but only if it represents deterioration.

LeBeau et al., 2000). Often with these approaches the asset is modelled as a system and a major failure of one component or set of components can lead to the complete failure of the asset. However, these types of models can be computationally expensive when considering large complex assets and are difficult to use for extended manifested deterioration processes (Khakzad et al., 2011; Rafiq et al., 2015).

Fernando et al. (2015) creates a Markov-based model which considers both the extended manifested deterioration and the latent deterioration processes. The condition scoring system considers seven system states, 1-5 are grouped as less severe and 6,7 are grouped as more severe. The deterioration matrix is divided into four parts: the top left quadrant describes deterioration between the less severe condition states in which both the extended manifested deterioration and the latent deterioration processes

are possible. The top right quadrant describes the movement from any of the less severe condition states to the more severe condition states, this is possible by latent deterioration processes only. The bottom left quadrant describes interventions from the more severe condition states back to the less severe condition states which, the authors state, would be done as a matter of urgency and therefore neither the extended manifested deterioration or the latent deterioration processes would be applicable. Finally, the bottom right quadrant describes the deterioration between the more severe condition states. In this quadrant it is assumed that any interventions would be carried out with urgency and therefore the only way of further deterioration occurring would be a repeat latent deterioration processes. The deterioration matrix is split to be calibrated for the extended manifested deterioration and the latent deterioration processes separately. The resulting Markov model is able to model both deterioration (manifested and latent) and intervention in a single time step as well as interactions between connected elements. A case study is investigated taking into account a short span steel box girder bridge asset. A number of intervention strategies are proposed depending on the condition and type of deterioration which affects the bridge. The analysis of the intervention strategies ranged from a minor repair at $56 \times 10^3 mu$ to failure of the asset due to a rock fall event at a cost of $1631 \times 10^3 mu$. The study concluded by stating that latent deterioration processes increase the probability of failure and therefore have associated increased costs. The authors mention that this is a necessary consideration to fully understand the deterioration processes that can affect the assets. On the other hand, the authors also mention that to properly assess the probability of latent deterioration, an extensive understanding of the operational, environmental and external factors around the assets must be known. Overall, the study provides a robust approach to considering natural hazards in what is typically a manifested deterioration focused modelling approach.

There is evidence to suggest that modelling the rare events and natural hazards around bridge management could provide a greater insight into the rapid failure of bridge assets. However, the absence of this data prevented any further developments at this stage.

The Deterioration Module controls the deterioration behaviour of the Sub-Minor Elements. The inputs to the module include the transition parameters which control the rate of deterioration of different defects. This module is arguably the most important as it contains the deterioration profile over time with typical usage. The SevEx conditions are represented in the module, seen in Figure 4.5, by the PN places. It should be noted that Figure 4.5 has been simplified so that only states A1 to C3 are shown, however the full details of each of the transitions can be seen in Table 4.1.

Tokens, representing bridge Sub-Minor Elements in this module, reside in the places corresponding their condition. For example, a Sub-Minor element that is in SevEx condition B3 will have a corresponding token in the place marked "B3". The transitions, shown as the grey squares, model the movement between conditions. In Figure 4.5, the transitions link the conditions together. $T1 - T8$ are stochastic transitions and their firing delay times are generated by statistical distributions. Over time, the tokens, representing Sub-Minor elements, will move from condition state A1 to B2 and then from B2 to B3, for example. One can notice in the figure that there are two coloured tokens, they represent two different elements at different stages of deterioration, B2 and B3 respectively.

The Deterioration Module connects to the Element Updating Module and the Intervention Module. When an intervention occurs, the Sub-Minor Element conditions are updated accordingly.

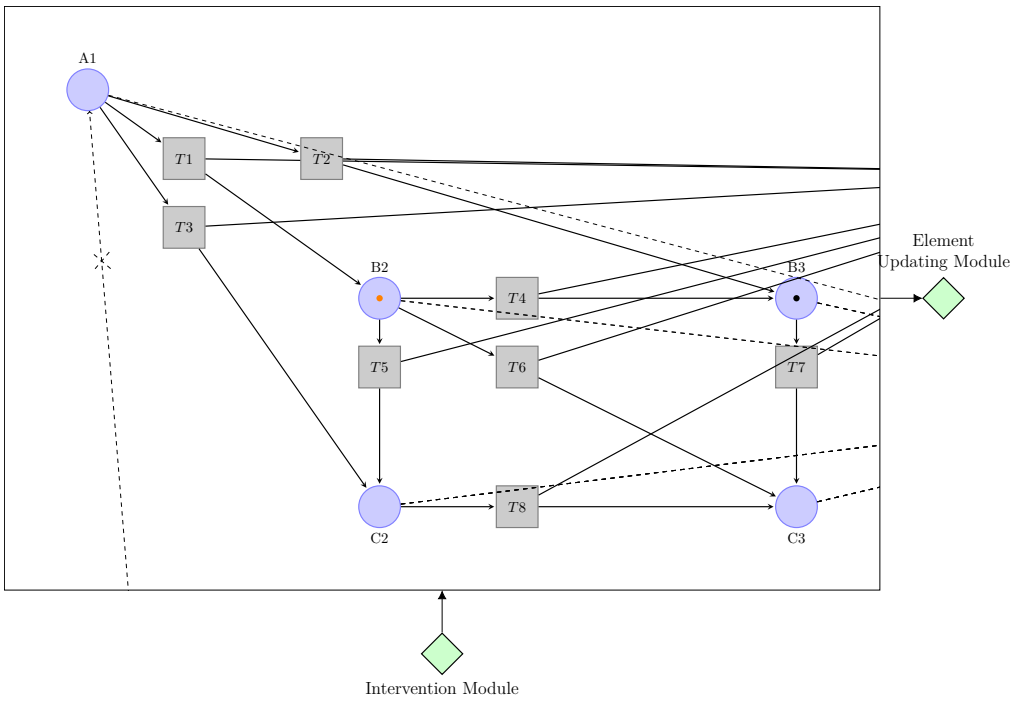


Figure 4.5: The deterioration module of the PN bridge model. Only states A1 to C3 are shown for clarity, however there are 31 states in total (A1 to G6).

Table 4.1: Table showing the transition properties for the Deterioration Module

Transition ID	From Condition	To Condition	Delay Type	Delay Distribution	Delay Parameter (λ, 1×10^3)	Source of Data
T1	A1	B2	Stochastic	Exponential	0.285111308	Historical Data
T2	A1	B3	Stochastic	Exponential	2.875533951	Historical Data
T3	A1	C2	Stochastic	Exponential	0.038706759	Historical Data
T4	B2	B3	Stochastic	Exponential	1.644246543	Historical Data
T5	B2	C2	Stochastic	Exponential	0.092423646	Historical Data
T6	B2	C3	Stochastic	Exponential	1.052437044	Historical Data
T7	B3	B4	Stochastic	Exponential	1.343750987	Historical Data
T8	B3	C3	Stochastic	Exponential	0.96587095	Historical Data

Table 4.1: Table showing the transition properties for the Deterioration Module

Transition ID	From Condition	To Condition	Delay Type	Delay Distribution	Delay Parameter (λ, 1×10^3)	Source of Data
T9	B3	C4	Stochastic	Exponential	0.382673435	Historical Data
T10	B4	B5	Stochastic	Exponential	1.988305582	Historical Data
T11	B4	C4	Stochastic	Exponential	0.358922794	Historical Data
T12	B4	C5	Stochastic	Exponential	0.251404067	Historical Data
T13	B5	B6	Stochastic	Exponential	1.561737677	Historical Data
T14	B5	C5	Stochastic	Exponential	0.469765758	Historical Data
T15	B5	C6	Stochastic	Exponential	0.106397277	Historical Data
T16	B6	C6	Stochastic	Exponential	0.265233782	Historical Data
T17	C2	C3	Stochastic	Exponential	3.078817734	Historical Data
T18	C2	D2	Stochastic	Exponential	0.478927203	Historical Data
T19	C2	D3	Stochastic	Exponential	0.399106003	Historical Data
T20	C3	C4	Stochastic	Exponential	1.091495839	Historical Data
T21	C3	D3	Stochastic	Exponential	0.753275241	Historical Data
T22	C3	D4	Stochastic	Exponential	0.236528423	Historical Data
T23	C4	C5	Stochastic	Exponential	1.025020126	Historical Data
T24	C4	D4	Stochastic	Exponential	0.295937585	Historical Data
T25	C4	D5	Stochastic	Exponential	0.110304008	Historical Data
T26	C5	C6	Stochastic	Exponential	0.542093154	Historical Data
T27	C5	D5	Stochastic	Exponential	0.138734739	Historical Data
T28	C5	D6	Stochastic	Exponential	0.123319768	Historical Data
T29	C6	D6	Stochastic	Exponential	2.510822272	Historical Data
T30	D2	D3	Stochastic	Exponential	4.926108374	Historical Data
T31	D2	E2	Stochastic	Exponential	0.136836344	Historical Data
T32	D2	E3	Stochastic	Exponential	0.957854406	Historical Data

Table 4.1: Table showing the transition properties for the Deterioration Module

Transition ID	From Condition	To Condition	Delay Type	Delay Distribution	Delay Parameter (λ, 1×10^3)	Source of Data
T33	D3	D4	Stochastic	Exponential	0.867887628	Historical Data
T34	D3	E3	Stochastic	Exponential	1.01432686	Historical Data
T35	D3	E4	Stochastic	Exponential	0.237795836	Historical Data
T36	D4	D5	Stochastic	Exponential	1.232913058	Historical Data
T37	D4	E4	Stochastic	Exponential	0.525436071	Historical Data
T38	D4	E5	Stochastic	Exponential	0.202727303	Historical Data
T39	D5	D6	Stochastic	Exponential	0.312518165	Historical Data
T40	D5	E5	Stochastic	Exponential	0.203500204	Historical Data
T41	D5	E6	Stochastic	Exponential	0.188964475	Historical Data
T42	D6	E6	Stochastic	Exponential	0.362983337	Historical Data
T43	E2	E3	Stochastic	Exponential	2.688172043	Historical Data
T44	E2	F2	Stochastic	Exponential	0.001000001	Historical Data
T45	E2	F3	Stochastic	Exponential	0.873655902	Historical Data
T46	E3	E4	Stochastic	Exponential	0.693471465	Historical Data
T47	E3	F3	Stochastic	Exponential	1.562079947	Historical Data
T48	E3	F4	Stochastic	Exponential	0.212287182	Historical Data
T49	E4	E5	Stochastic	Exponential	1.245824464	Historical Data
T50	E4	F4	Stochastic	Exponential	1.040468719	Historical Data
T51	E4	F5	Stochastic	Exponential	0.39017578	Historical Data
T52	E5	E6	Stochastic	Exponential	0.860114134	Historical Data
T53	E5	F5	Stochastic	Exponential	0.596215498	Historical Data
T54	E5	F6	Stochastic	Exponential	1.07514269	Historical Data
T55	E6	F6	Stochastic	Exponential	0.761035008	Historical Data
T56	F2	F3	Stochastic	Exponential	4.436151798	Historical Data

Table 4.1: Table showing the transition properties for the Deterioration Module

Transition ID	From Condition	To Condition	Delay Type	Delay Distribution	Delay Parameter (λ, 1×10^3)	Source of Data
T57	F2	G2	Stochastic	Exponential	0.248756219	Historical Data
T58	F2	G3	Stochastic	Exponential	0.001000001	Historical Data
T59	F3	F4	Stochastic	Exponential	0.948017544	Historical Data
T60	F3	G3	Stochastic	Exponential	0.149838634	Historical Data
T61	F3	G4	Stochastic	Exponential	0.008644537	Historical Data
T62	F4	F5	Stochastic	Exponential	2.875033782	Historical Data
T63	F4	G4	Stochastic	Exponential	0.001000001	Historical Data
T64	F4	G5	Stochastic	Exponential	0.068250068	Historical Data
T65	F5	F6	Stochastic	Exponential	2.770798444	Historical Data
T66	F5	G5	Stochastic	Exponential	0.083752094	Historical Data
T67	F5	G6	Stochastic	Exponential	0.446677834	Historical Data
T68	F6	G6	Stochastic	Exponential	0.088856081	Historical Data
T69	G2	G3	Stochastic	Exponential	0.487329435	Historical Data
T70	G3	G4	Stochastic	Exponential	0.661375661	Historical Data
T71	G4	G5	Stochastic	Exponential	0.683060109	Historical Data
T72	G5	G6	Stochastic	Exponential	3.245067497	Historical Data

4.1.2 Element Updating Module

The element updating module is designed to mimic the hierarchy that NR have built into their bridge management procedures. NR inspect each Sub-Minor element of a bridge and records its condition according to SevEx. However, maintenance policies are decided upon at the Minor element level, not the Sub-Minor element level. This means that there has to be a transla-

tion of conditions up the hierarchy and this module is used for that purpose. The module takes the subordinate (Sub-Minor) element conditions and determines the superior (Minor) elements condition. This module follows the decision making hierarchy laid out by Network Rail (2010e).

The PN module shown in Figure 4.6 has a trigger place ("Condition Change") which initiates the module. The full details of the transitions can be seen in Table 4.2. The transition marked $T74$ contains a number of advanced features signified by dashed input and output arcs. The transition analyses the marked input places linked via dashed input arcs and then can either choose the worst condition or the median condition depending on the element type currently being looked at. For instance, if the element was a structural beam, then the Sub-Minor elements would be the sections of the beam. In that situation the transition would take the worst Sub-Minor element condition and set it as the condition of the Minor element because it is the most critical section of the beam. However, if the element in question was a masonry wall, then the updater function would take the median Sub-Minor element condition and set it as the condition of the Minor element because it is more structurally appropriate. The updater module is designed to be triggered every time that a Sub-Minor element degrades so that the Minor element condition is always kept up to date.

Table 4.2: Table showing the detailed transition configuration within the Element Updating Module

Transition ID	Place From	Place To	Delay Type	Transition Functions	Source
T73	Condition Change, Condition Determined	Pending Condition	Instant	Reset	PN Convention
T74	Pending Condition	Condition Determined	Instant	Condition Transpose	Expert Opinion

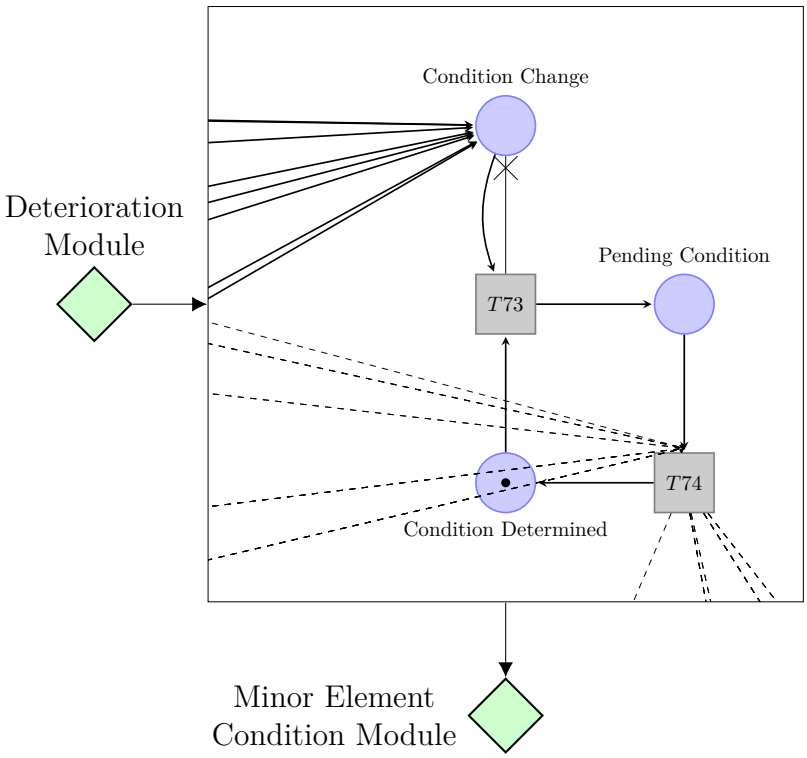


Figure 4.6: The element updating module shown connected to the corresponding places in Figure 4.5.

4.1.3 Inspection Module

The inspection module models the inspection process of minor elements. The inspection module follows guidelines set out in Network Rail (2010d). It uses the SevEx condition to determine when the next inspection should take place; the SevEx conditions and their corresponding inspection frequencies are shown in Table 4.6. The inspection module in the PN, seen in Figure 4.7, uses the same condition based inspection regime found in Table 4.6. Transition $T75$ uses dashed input arcs to analyse Minor element conditions. Depending on the marking of the places in the Minor Element Condition Module, the transition firing delay is determined. Elements that are in a poorer condition are deemed to require more close monitoring than those in a better condition. Full details of the transition information can be seen in Table 4.3.

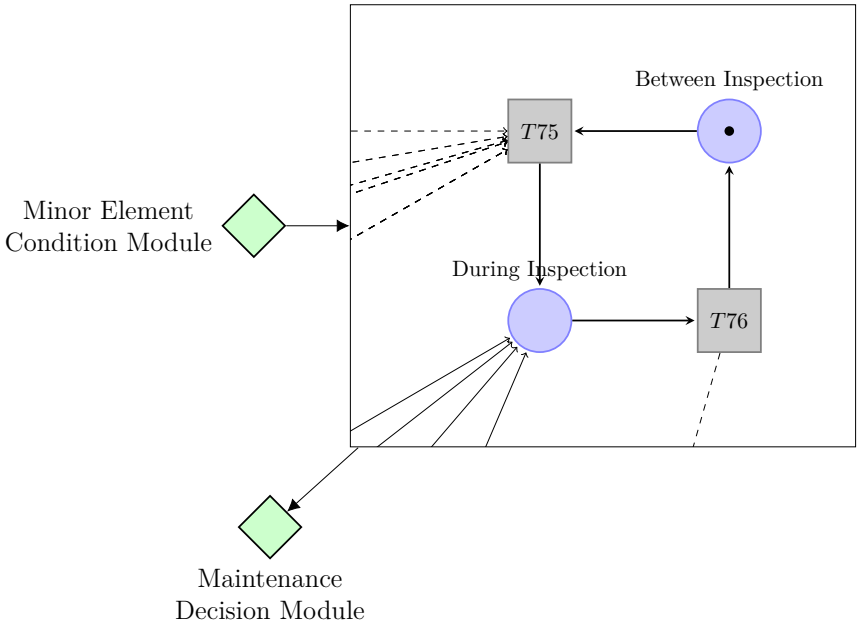


Figure 4.7: The inspection module shown using the most recent policy from Network Rail (2010b).

Table 4.3: Table showing the detailed transition configuration within the Inspection Module

Transition ID	Place From	Place To	Delay Type	Transition Functions	Source of Data
T75	Between Inspection	During Inspection	Conditional, see Table 4.6		Network Rail (2010d)
T76	During Inspection	Between Inspection	Small Delay (η)	Reset	Assumed

4.1.4 Maintenance Decision Module

The maintenance decision module, seen in Figure 4.8, mimics the process after an inspection has occurred. Once the inspection has occurred and the condition of the elements has been determined, policy documents then detail what the most appropriate maintenance action is (Network Rail, 2012a). These decisions occur at the Minor element level. This is replicated in the module using transitions $T77$-$T106$ which are only activated when triggered by the inspection module. Full details of the transition information can be seen in Table 4.4. The place labelled "Inspection Occurred" is marked once an inspection occurs and inhibits the transitions from firing again to avoid re-triggering. Once the inspection has taken place, the corresponding maintenance action is then scheduled. There are three possible maintenance actions. These are represented in Figure 4.8 by the places labelled: "Minor Repair Required", "Major Repair Required" and "Replacement Required". Each of the SevEx conditions leads to the corresponding maintenance action e.g. a Minor Element which has been inspected and determined to be in SevEx condition D2 would require a Minor Repair. Therefore, the place labelled "Minor Repair Required" would be marked in the module. This decision is simulated in the model and depends on the element condition, as described in Section 2.2.3.7.

Table 4.4: Table showing the transition properties for the maintenance decision module

Transition ID	Place From	Place To	Source of Data
T77	B2	Minor Repair Required	Converted, see Section 4.2.3
T78	B3	Minor Repair Required	Converted, see Section 4.2.3
T79	B4	Minor Repair Required	Converted, see Section 4.2.3
T80	B5	Major Repair Required	Converted, see Section 4.2.3

Table 4.4: Table showing the transition properties for the maintenance decision module

Transition ID	Place From	Place To	Source of Data
T81	B6	Major Repair Required	Converted, see Section 4.2.3
T82	C2	Minor Repair Required	Converted, see Section 4.2.3
T83	C3	Minor Repair Required	Converted, see Section 4.2.3
T84	C4	Major Repair Required	Converted, see Section 4.2.3
T85	C5	Major Repair Required	Converted, see Section 4.2.3
T86	C6	Major Repair Required	Converted, see Section 4.2.3
T87	D2	Minor Repair Required	Converted, see Section 4.2.3
T88	D3	Major Repair Required	Converted, see Section 4.2.3
T89	D4	Major Repair Required	Converted, see Section 4.2.3
T90	D5	Major Repair Required	Converted, see Section 4.2.3
T91	D6	Replacement Required	Converted, see Section 4.2.3
T92	E2	Major Repair Required	Converted, see Section 4.2.3
T93	E3	Major Repair Required	Converted, see Section 4.2.3
T94	E4	Major Repair Required	Converted, see Section 4.2.3
T95	E5	Replacement Required	Converted, see Section 4.2.3
T96	E6	Replacement Required	Converted, see Section 4.2.3
T97	F2	Major Repair Required	Converted, see Section 4.2.3
T98	F3	Major Repair Required	Converted, see Section 4.2.3
T99	F4	Replacement Required	Converted, see Section 4.2.3
T100	F5	Replacement Required	Converted, see Section 4.2.3
T101	F6	Replacement Required	Converted, see Section 4.2.3
T102	G2	Replacement Required	Converted, see Section 4.2.3
T103	G3	Replacement Required	Converted, see Section 4.2.3
T104	G4	Replacement Required	Converted, see Section 4.2.3

Table 4.4: Table showing the transition properties for the maintenance decision module

Transition ID	Place From	Place To	Source of Data
T105	G5	Replacement Required	Converted, see Section 4.2.3
T106	G5	Replacement Required	Converted, see Section 4.2.3

4.1.5 Intervention Module

The intervention module, shown in Figure 4.9, is the most complex module as it contains a number of advanced CPN functions. The intervention module initiates when a maintenance action has been decided upon in the Maintenance Decision Module. Once the trigger place, "Intervention Planned", has been marked, this enables the rest of the module to function. Transition $T17$ is designed to be flexible to have a flexible delay time depending on the type of maintenance action which has been scheduled. Each maintenance action has a different amount of delay whilst the possession of the asset is requested and the materials ordered. These delay times are obtained from historical data and embedded into Transition $T107$. This enhanced functionality is shown in the figure with dashed input arcs. Full details of the transition information can be seen in Table 4.5.

Transition $T108$ is designed to simulate a maintenance team going out to perform the maintenance. When the team get to the site, the first task is to assess the deteriorated elements. This is represented in the model by dashed input arcs from the Minor element condition places to determine the token position. The maintenance teams will have obtained and prepared the resources for the maintenance action that was scheduled. If the element is in the condition they were expecting, then the work can commence and

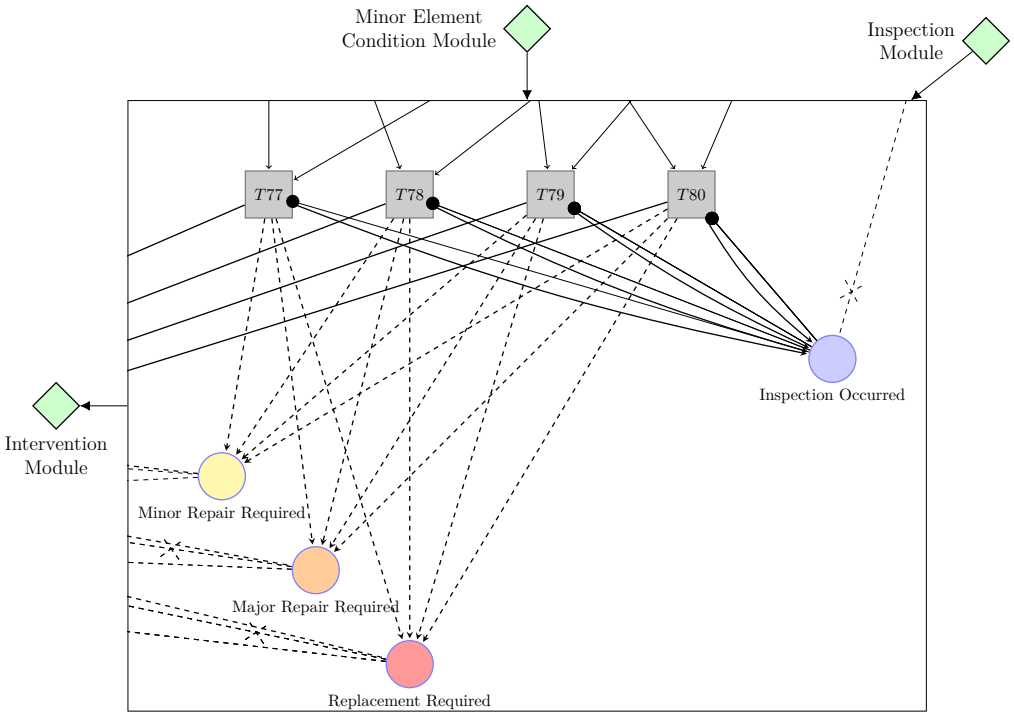


Figure 4.8: The maintenance decision module. Only Transitions $T77 - T80$ are shown for clarity, however there are 31 Transitions relating to condition states A1-G6.

the condition of the element will improve accordingly.

An important addition to the model is the possibility of not being able to carry out the scheduled maintenance action. In practice, this is a common occurrence. If the maintenance team arrive on site, inspect the element and the condition of the element has deteriorated beyond that which they were expecting; then the maintenance team will not have the necessary time or resources to repair the element. For instance, if the possession time requested was 6 hours and the element has degraded to the point where 8 hours are required to carry out the work, then maintenance must be postponed. In this situation, the maintenance action must be re-scheduled and the maintenance teams must return. This functionality makes the intervention module one of the most complex, but enhances the realism of the model.

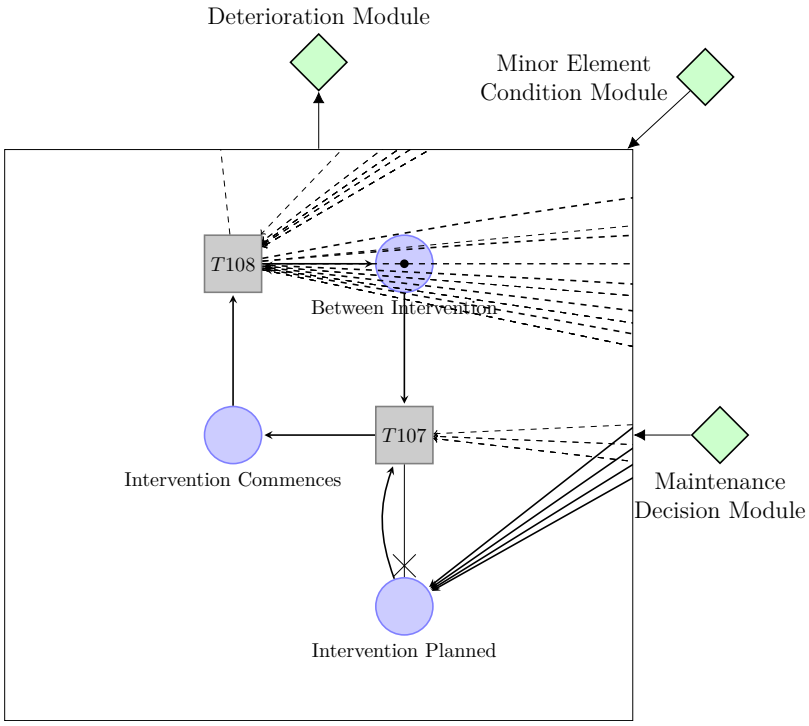


Figure 4.9: The intervention module has a number of advanced features, shown with dashing input and output arcs, to mimic the complex processes involved in repairing elements.

Table 4.5: Table showing the detailed transition configuration within the Intervention Module

Transition ID	Place From	Place To	Delay Type	Transition Functions	Source of Data
T107	Between Intervention, Intervention Planned	Intervention Commences	Conditional, see Table 4.11	Reset	Historical Data, Expert Opinion
T108	Intervention Commences	Between Intervention	Conditional, see Table 4.11	Reset, Conditional Intervention	Expert Opinion, Industry Guidelines

4.2 Module Parameter Estimation

The model framework has been presented and explained module by module. The framework structure follows the NR bridge management procedures and policies. However, some of the modules features and parameters depend on real world data, typically from historical records. For aspects of the model where there was no available data, industry expert knowledge was used.

4.2.1 Data Source

A variety of different datasets were used for this study: the Cost Analysis Framework (CAF), the Civil Asset Register and Reporting System (CARRS), MONITOR and the Structure Condition Marking Index (SCMI). CAF contains larger items of repair work, including details of the condition and the work required. CARRS contains general asset information for portfolio overviews, used mainly for system level observations. MONITOR is similar to CAF, however is used for smaller items of work carried out by NR maintenance teams. Finally SCMI contains the inspection records, including both the SevEx and SCMI scores. Although the exact data cannot be distributed for confidentiality reasons, representations of the data sets used in this research are given in Section B.1.

A number of different dataset cuts were used, some of which initially overlapped in their contents. Additionally, each dataset was presented in a different digital format. An SQL Server was created to house all the data. The data first needed to be cleansed of erroneous records and converted to the same data types:

- Data Type Conversions:
  - Mileage, yards and chainage into metres
  - Homogenisation of Date and time formats

  - Re-categorisation of free text fields

- Erroneous Records:
  - Dates that were in the future
  - Records pre-dating inspections
  - Scores outside the SevEx scope

- Identification Codes
  - Valid within same dataset
  - Not compatible between datasets
  - New Globally Unique Identifier (GUID) created

To make sure the data cleansing/combing was carried out correctly, a small sample set of data was taken from each of the datasets and SQL queries written to combine the datasets into one coherent database. This was carried out rigorously to make sure that duplicate records were not present within individual datasets or across multiple datasets. Once the queries had been validated the complete datasets could be combined. A Globally Unique Identifier (GUID) had to be created as the identification codes between databases were incompatible. To achieve this, the same element between databases could be matched on the: ELR, Mileage, Major Element Code, Major Element No., Minor Element Code, Minor Element No., Structure Type and Material.

This process allowed the SQL database to be cleansed of erroneous data, combined the datasets into one coherent database and to verify that there were no duplicate entries. Any questionable entries were checked with industry experts. The final combined dataset spanned from 1998 to 2014.

NR use an element hierarchy to organise their assets. The total number of inspected bridges is 25,949. Each asset is divided into a number of different Major Elements e.g. deck, end supports and mid supports. The

Major Elements are element groups rather than distinct elements. There are 273,427 inspected Major Elements in the database. Each of the Major Elements are split up into Minor Elements e.g. bearings, girders and wing walls. There are 563,150 Minor Elements that have been inspected. These quantities have been structured in Figure 4.10.



Figure 4.10: Element hierarchy and the associated quantity. Quantities calculated from the available data sets.

Concrete girders are used in this research as the example element. This is because concrete structures are becoming more common and so their management is becoming more important. The number of concrete bridges in the database totals 4,434. These are the primary load bearing elements and so are critical to the health of the structure. The total number of inspections on concrete main girders is 407,708.

4.2.2 Inspection Module Parameter Estimation

Section 2.2.3.7 describes how the SevEx condition of the element is converted to the SCMI and then to a risk level that corresponds to an inspection interval. Rather than have to carry out this process, a back-calculation was carried out so that the inspection interval could be directly related to the SevEx condition state. This was then incorporated into the model so that the inspection schedule could be determined during simulation. Table 4.6 shows which SevEx states relate the corresponding inspection interval for concrete elements. Assets which are in better condition, and therefore have higher SevEx ratings, are deemed to be lower risk and so are subjected to 12 year inspection intervals. Assets which are in a medium condition have inspections every 6 years. Finally, elements rated in the worse SevEx

states are deemed to have a higher risk and must be inspected every 3 years.

The cost of inspections, $30mu$, was extracted and converted from the NR Tier 2 Structures Model.

Table 4.6: Table showing the SevEx states and their corresponding inspection interval

Interval (years)	States
12	A1, B2-B5, C2-C3, D2
6	B6, C4-C6, D3-D5, E2-E5, F2-F3
3	D6, E6, F4-F6, G2-G6

4.2.3 Maintenance Decision Module Parameter Estimation

To determine the correct maintenance action, the standard NR bridge maintenance policies were used (Network Rail, 2012a). As described in Section 2.2.3.8, they provide the threshold conditions for the suitable type of maintenance. The document provides different thresholds for different material types.

Equivalent thresholds were used in the model. For example, the threshold $D3$ is provided in Network Rail (2012a) for when Major Repair should be carried out on concrete elements, which relates to an SCMI score of 70. Therefore, the other SevEx conditions were compared against this level to determine which maintenance action would be recommended. This was carried out so that the appropriate maintenance action could be determined directly from the SevEx score during simulation. These are shown in Table 4.7 where each SevEx condition has its corresponding maintenance action.

Table 4.7: Table showing the SevEx state thresholds for different maintenance actions.

Maintenance Action	States
Minor Repair	B2-B4, C2-C3, D2
Major Repair	B5-B6, C4-C6, D3-D5, E2-E4, F2-F3
Replacement	D6, E5-E6, F4-F6, G2-G6

4.2.4 Deterioration Module Parameter Estimation

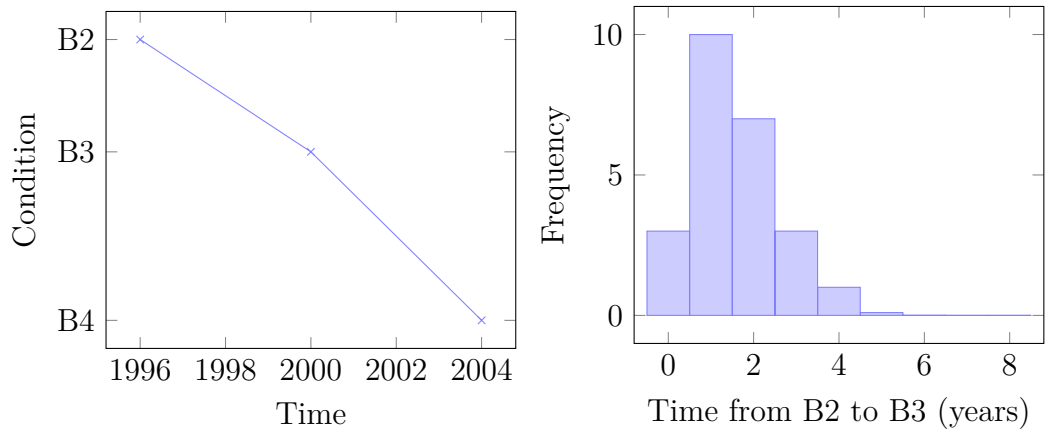
The historic condition data must be processed into the format required for the model. By aligning the historic data in a suitable format for the model, it is possible to combine the NR policies and historic data to create a more comprehensive model.

To be able to calibrate the deterioration profile, a change in the condition of the element is required. This means elements need to have at least two inspections to be used for deterioration parameter estimation. The population of assets is vast and it takes a significant amount of time to inspect every one and so most of the elements that have had repeat inspections have only two inspections, accounting for 82.68% of all elements. Some elements have had three repeat inspections (15.83%), presumably they are in regions that have enough resources to inspect their structures more often; or the structure is on a particularly critical route. Elements inspected very frequently often suggest that there is an inherent aggressive defect with the structure that needs to be monitored extensively. Elements that have been subjected to 4-6 inspections (1.49%) are not typical of the population.

4.2.4.1 Time-Based Data Fitting

One way to format the historic data is to use a time-based approach (Agrawal et al., 2010; Niroshan et al., 2014), which is also typically used with PNs (Rama and Andrews, 2013a). Each structure is routinely in-

spected and so a record can be built up of the condition of each element that the structure comprises of. Changes in the condition of each element can be plotted, as seen in Figure 4.11a. The historical records are from the perspective of specific elements i.e. recording the condition of the element at different points in time. However, for this approach, the perspective is on the time it takes to move from one condition to another so the records have to be de-constructed and amalgamated into the frequency of occurrence, as seen in Figure 4.11b.



(a) An example of an elements historical condition over time.

(b) An example of amalgamated times to move from B2 to B3.

Figure 4.11: An example of historical conditions of an element; and then the amalgamated times to move from one condition state to another.

The de-constructed data can then be used to fit lifetime distributions to. This can then be used in the PN model to be able to generate transition times with similar characteristics to the original data.

However, this approach is unsuitable in this situation because the inspection intervals are comparatively large. This means that there is a large discrepancy between the revealed and un-revealed state of the structure. It is only during inspection that the revealed state of the structure is determined and recorded. An example of the discrepancy between the actual condition of the structure and the assumed condition is shown in Figure 4.12 and the corresponding Table 4.8. The "True Condition" in this case

refers to an idealised un-revealed condition of the element while the ”Assumed Condition” is the condition as revealed upon the latest inspection. The column ”Correct/Incorrect” is simply a boolean indicator to indicate whether the True Condition of the asset is the same as the Assumed condition. It can be seen that when the rate of deterioration is slow, the Assumed Condition mostly matches that of the True condition. However, as the rate of deterioration increases, the Assumed condition becomes less accurate to the True condition.

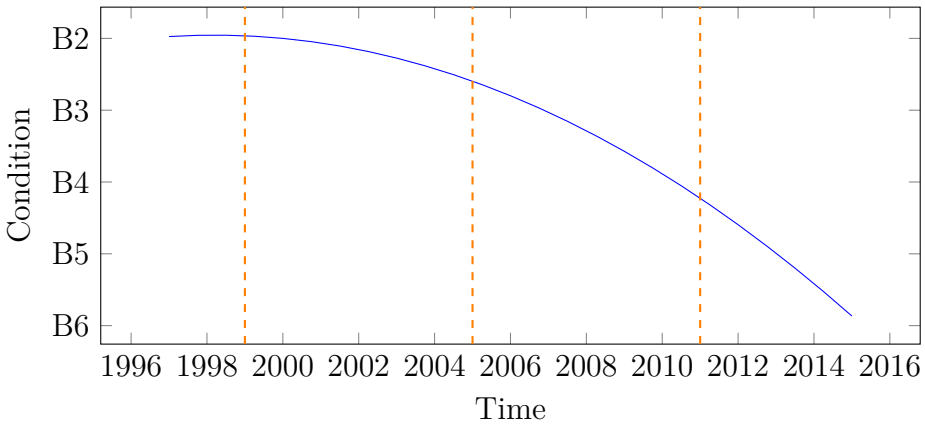


Figure 4.12: An example of the historical condition of an element where the blue line represents the actual condition of the structure and the dashed orange lines represent the inspection occurrences every 6 years.

The inspection intervals are large compared to the time it takes to move between condition states. This results in a lack of precision in knowing when there was a change in condition. Figure 4.12 and Table 4.8 shows the disadvantage of using this approach with a fictitious example. When the deterioration is slow e.g. in the B2 condition state of the example, the ~6 year standard inspection interval adequately oversees the deterioration of the structure, but when the deterioration quickens, the inspection interval is not adequate leading to “jumps” in defect condition e.g. inspections completely miss the B3 condition state. In summary, due to the limitations of the data, lifetime distributions cannot be obtained. Therefore, the movement between condition states of the structure is assumed to be of a

Year	True Condition	Assumed Condition	Correct/Incorrect
1997	B2	A1	Incorrect
1998	B2	A1	Incorrect
1999	B2	B2	Correct
2000	B2	B2	Correct
2001	B2	B2	Correct
2002	B2	B2	Correct
2003	B2	B2	Correct
2004	B2	B2	Correct
2005	B2	B2	Correct
2006	B2	B2	Correct
2007	B3	B2	Incorrect
2008	B3	B2	Incorrect
2009	B3	B2	Incorrect
2010	B4	B2	Incorrect
2011	B4	B4	Correct
2012	B4	B4	Correct
2013	B5	B4	Incorrect
2014	B5	B4	Incorrect
2015	B5	B4	Incorrect

Table 4.8: Table, corresponding to Figure 4.12, showing the difference in actual and assumed condition when the inspection intervals are disproportionate to the time it takes to move between states. State A1 is the "new" state which is taken as the assumed state for new structures before their first inspection.

constant rate.

Most models that incorporate structural deterioration use a one dimensional condition state scale e.g. new, good, poor (Cesare et al., 1992; Morcous, 2006; Le and Andrews, 2014). However, structures fail by multiple failure modes, as seen in Table 2.1. Different defects deteriorate at different rates and are more or less likely to lead onto other defects. For this reason keeping the failure modes separate was an important part of the deterioration module. This research uses the SevEx condition system, a 2-D condition scale comprising the defect type and the magnitude of the defect. Although this approach enhances the realism of the deterioration, it also makes parameter estimation more difficult.

There has also been a review of the time steps used in the model. NR inspect their structures roughly every 6 years, however for the model a more regular time step is required. Additionally, having a smaller time step should give more transparency to the model as deterioration can be followed more closely. The following assumption has been implemented: the condition of an element can only move to the immediately neighbouring states. To satisfy this assumption, a time step of one month was selected as it was seen as the longest unit of time that would not enable an element to move beyond one condition state. Most bridge management models (Le and Andrews, 2013; Agrawal et al., 2010; Cesare et al., 1992) choose 1 year time steps, however this would not satisfy the constraint previously mentioned, in particular regarding duration of maintenance actions. Figure 4.4 shows the condition states with the movements that are possible between them.

In practice, the element condition movements have been calculated from historic data. The assumption being used is that the condition of an element can only move to the immediately neighbouring states because of the monthly time interval. The Mean Time to Failure (MTTF) was then calculated (Alessandro, 2010) for the positions being considered, using the following equation:

$$MTTF_{B2\rightarrow B3} = \frac{t \cdot n_{B2}}{m_{B2\rightarrow B3}} \tag{4.1}$$

where t is the time interval, in this case 72 months between inspections, n_{B2} is the total number of elements residing in state $B2$ at the beginning of the time interval, and $m_{B2\rightarrow B3}$ is the number of elements that move from $B2$ to $B3$. The MTTF is then used to calculate (Alessandro, 2010) the failure rate:

$$\lambda_{B2\rightarrow B3} = \frac{1}{MTTF_{B2\rightarrow B3}} \tag{4.2}$$

where λ is the failure rate. Here $\lambda_{B2\rightarrow B3}$ represents the rate of an ele-

ment moving from state $B2$ to $B3$. Historical data was used to obtain the occurrences between each condition state e.g. the number of elements that move from condition B2 to condition B3. These were then used to compute the MTTFs and subsequently, the rates i.e. λ values. Each transition is assigned its corresponding λ value which is then used to generate the transition time in the PN deterioration module from the exponential distribution. Some of these values can be seen in Table 4.9.

Table 4.9: Extract of the movements from state to state along with the MTTF and corresponding failure rate.

State From, To	Number of Occurrences	MTTF (years)	Failure rate (years,10^{-2})
A1,B2	2335	292.2835	0.3421
A1,B3	23550	28.9801	3.4506
A1,C2	317	2152.9400	0.0464
B2,B3	1103	50.6817	1.9731
B2,C2	62	901.6451	0.1109
B2,C3	706	79.1813	1.2629
B3,B4	5046	62.0154	1.6125
B3,C3	3627	86.2779	1.1590
B3,C4	1437	217.7661	0.4592

The deterioration profile for concrete girders, the critical element in this research, was simulated in the model and can be seen in Figures 4.13 and 4.14. Figure 4.13 shows the probability of being in different conditions over time with no intervention. This is useful to be able to see how defects evolve over time. Figure 4.14 shows which maintenance action would be required in each year of the simulation. In this example, no rehabilitation is available. The simulation was performed with the element starting in a new (A1) condition.

Quality of Fit of the Deterioration Module To perform parameter estimation of the deterioration of the concrete main girders, the data was randomly split into two sets. The total dataset included 407,708 re-

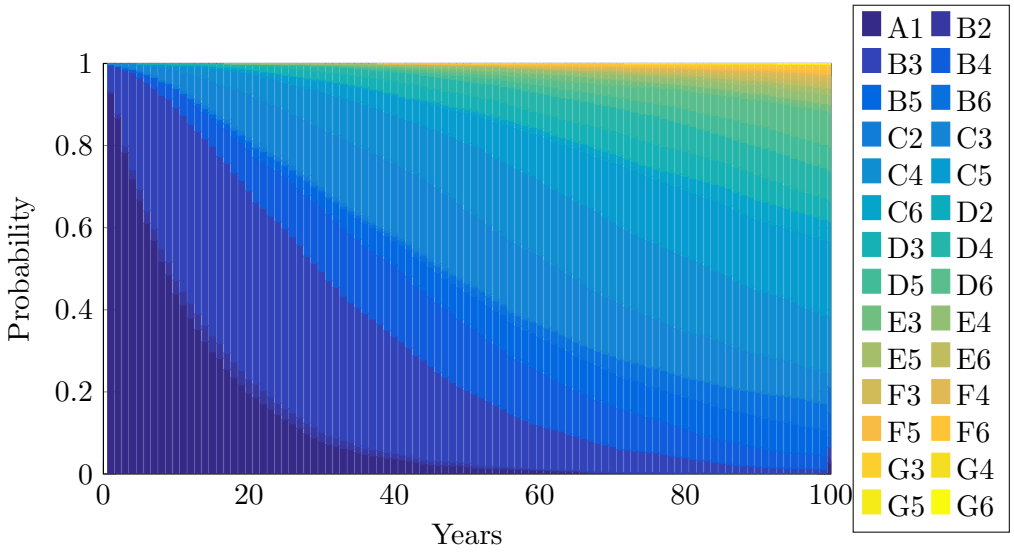


Figure 4.13: A demonstration of the deterioration of a concrete girder, the critical element in this research. The element begins the simulation in a new (A1) condition. The graph shows the probability of being in different condition states over time.

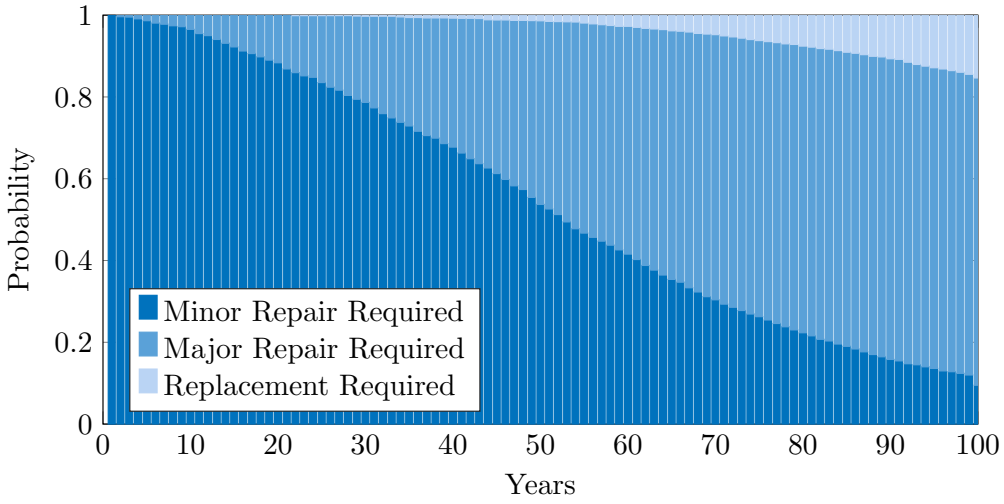


Figure 4.14: The graph shows the probability of which maintenance action would be required, if they were available, at any given time over the 100 year simulation period. In this example, no maintenance actions are available.

peat inspection records and a random sample of 75% (305,781 records) was chosen as the parameter estimation dataset. The remaining 25% (101,927 records) was used as a test dataset. Micevski et al. (2002) states that split sample analysis is a robust test as it uses historical data not considered in the parameter estimation dataset which makes them independent. The parameter estimation dataset was used to generate the failure rates, λ, which are the parameters embedded in the model transitions. The results were compared with the test data to see if the results were independent of one another based on the χ^2 test. The χ^2 test uses the following equation:

$$\chi^2 = \sum_{i=1}^{n} \frac{(Obs\lambda_i - Exp\lambda_i)^2}{Exp\lambda_i} \tag{4.3}$$

where χ^2 is the Pearson's cumulative test statistic; n is the number of λ parameters; $Obs\lambda_i$ is the observed failure rate and $Exp\lambda_i$ is the expected failure rate. The test was carried out at the 5% significance level and only movements from state to state with occurrences greater than 5 were considered (Cochran, 1954). The resulting p-value was <0.001 which suggests that the deterioration module passes the goodness-of-fit test using the calibrated and test data sets.

4.2.5 Intervention Module Parameter Estimation

This module requires parameter estimation regarding 1) the delay time between requesting a maintenance action and it occurring and 2) the cost of the interventions. Using historical data and expert judgement, the monetary unit costs of intervention are presented in Table 4.10. In the model, for interventions, the "Response Time" is considered the sum of the scheduling delay and the time to perform the rehabilitation ("Work Time"). The scheduling delay is the time associated with ordering the materials and requesting possession of the structure. The CAF and Monitor records were used to calculate these time delays and were then checked and discussed

with industry experts. The Response Times, presented in months, can be seen in Table 4.11.

Table 4.10: Intervention costs, presented in monetary units, calculated based on historic data and expert judgement.

	Minor Repair	Major Repair	Replacement
Cost (mu)	140	400	1,500
Source	Monitor	CAF	CAF

Table 4.11: Response Time which is considered the sum of the scheduling delay and the time to perform the rehabilitation ("Work Time"), calculated from historic data and expert judgement. All units are in months.

Intervention Type	Response Time	Scheduling Time	Work Time
Minor Repair	4.00	3.90	0.10
Major Repair	23.20	18.63	4.57
Replacement	27.52	22.63	4.89

4.2.6 Summary of Module Parameter Estimation

An understanding of the complex deterioration process is crucial in calibrating the model. The NR inspections were carried out approximately every 6 years. This interval is not frequent enough to accurately determine when the condition of the structure has changed between the condition states. Therefore, often the defects seem to "jump" to worse condition states because of the fact that the inspection interval is not frequent enough to capture the precise moment an element moves from one condition to another. For this reason lifetime distributions cannot be obtained and so a constant rate of deterioration was assumed in the Deterioration Module.

With the Inspection Module and Maintenance Decision Module, the current industry policies were back-converted to be able to be incorporated into the model directly. This then allows dynamic inspection intervals (i.e. changeable) as well as a multitude of maintenance actions to be simulated along with the structural deterioration. Finally, the Intervention Module

was calibrated with the maintenance records and expert judgement to provide the costs, scheduling and rehabilitation times for the model.

4.3 Sample Model Outputs

Example simulations of the model can be run to show the effects of deterioration, inspection and intervention and how they interact. An asset has many components that each have their own deterioration profile. For the example simulation shown in the outputs below, a single concrete main girder is presented for clarity. The model is configured with the current NR practices and policies and the element begins the simulation in the A1 condition. The NR intervention strategy selected is quite rigorous; whenever the structure is below an A1 condition, it is eligible for repair.

MC samples are used in the model for: 1) generating the stochastic transition times, 2) resolution of PN conflicts and 3) certain decision transition features. This means that MC simulations are used to evaluate the probabilistic performance of the system. The stochastic transitions are mostly used in the Deterioration Module. The drawback of using this approach is the high computational cost which results from having to execute enough MC simulations to ascertain the average system performance. This section provides model outputs, produced after model simulation, to gain an understanding of the average system performance.

Figure 4.15 shows the probability of being in different states over time. As the element starts in a good condition, the chance of it being in a good condition is high to begin with. An element in condition A1 would be inspected after 12 years, at which point it could have degraded to a worse state. At the 12 year point, it would be inspected and subsequently maintained, hence the increase in the expected condition at roughly 12 years. The graph then takes on a saw-tooth pattern where the structure degrades until it gets inspected and potentially maintained. The frequency

of this saw-tooth is the same frequency as the inspection regime modelled. Some of the sawtooths are not perfectly smooth due to the stochastic nature of the deterioration process. In some of the simulations the deterioration has been more severe and so the inspection regime has changed to either 3 or 6 years depending on its condition, hence the more regular interventions.

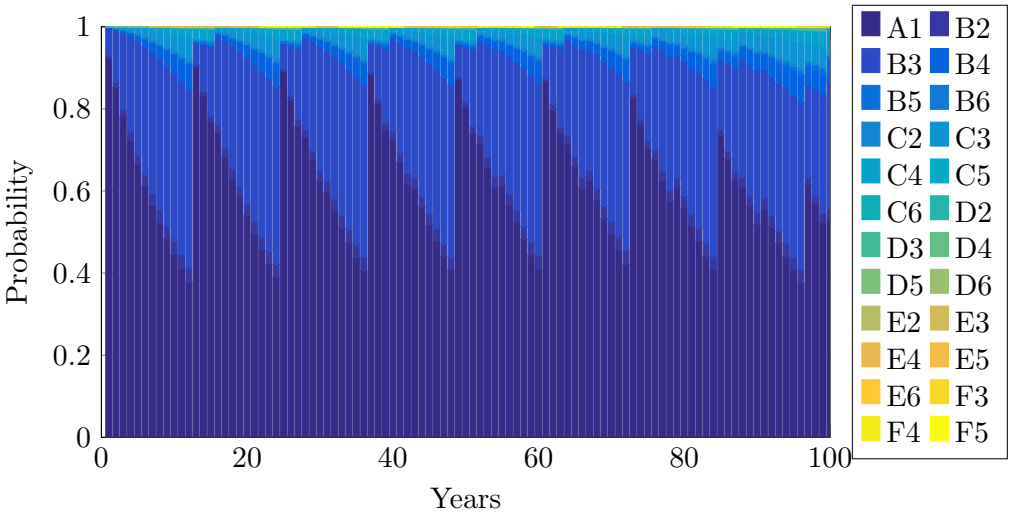


Figure 4.15: Graph to show the probability of being in different states over time.

Figure 4.16 shows the probability of the element being in different condition states. This example has the starting condition being in a good state, hence the high probabilities of it occupying the better condition states. When the element degrades, it only gets so far before it is inspected and then maintained, which is why it rarely strays into the worse condition states. This graph also incorporates the 99% confidence intervals to show the confidence in the probabilities of it residing in certain states. This graph is useful to see the range of states that the element can occupy over the simulation time.

Figure 4.17 shows the probability of each intervention type per year over the simulation period. This graph only shows which intervention type would be required considering the condition of the element, not what interventions have been carried out. Considering this example starts with an

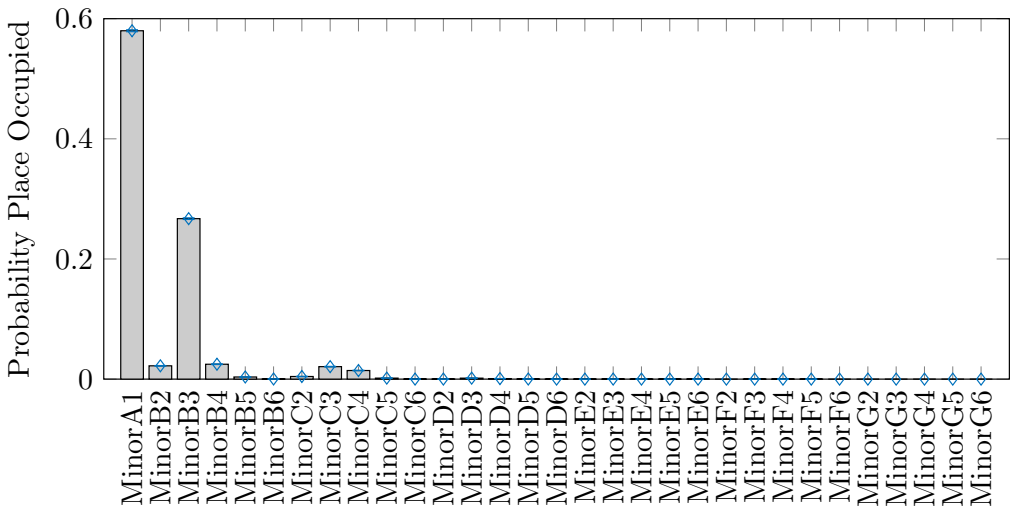


Figure 4.16: Graph to show the probability of the element being in different condition states.

element in $A1$ condition, the vast majority of the graph shows that only minor repairs would be required. It can be noticed that there are some major repairs developing over time as the element ages. Lastly, there is a minimal probability of the element requiring a replacement. This is useful for being able to plan work items and predict work schedules, an essential feature to support railway bridge management decision making.

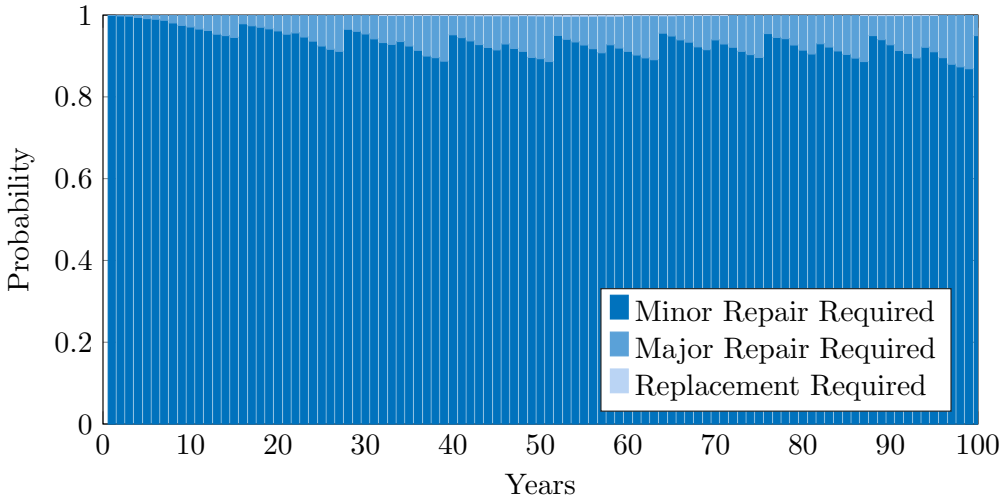


Figure 4.17: Graph to show the probabilities of different types of intervention over time.

Figure 4.18 shows the nominal and cumulative cost per year of interventions and inspections. This graph only shows the cases where intervention has been carried out. The bars of the stacked bar chart are regular to the 12 year frequency, as seen in Figure 4.15. The bars are split into the cost of Minor Repairs, Major Repairs and Replacements. There are actually very few replacements, but due to their high cost, their effect seems disproportionate. This graph is useful to visualise the Whole Life-Cycle Costing (WLCC) of the structure, allowing a railway bridge manager to understand when and where the major costs are coming from. Being able to predict future costs is a vital feature for bridge portfolio managers.

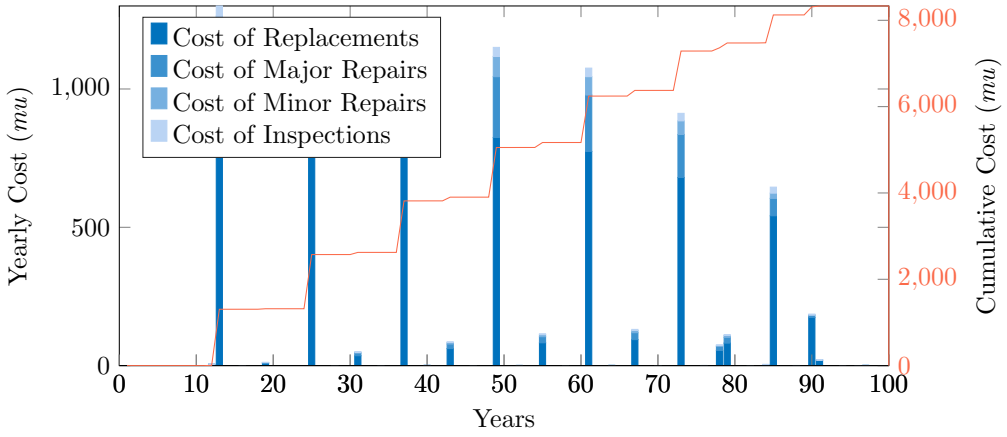


Figure 4.18: Graph to show the nominal and cumulative cost per year of interventions and inspections.

Figure 4.19 shows the distribution of cumulative costs from each simulation. In this example, 2000 simulation samples were obtained. The graph shows the cumulative cost from each simulation compiled as a histogram. This graph is useful to show the amount of confidence in the final result. In the graph, it can be seen that ~55% of the outcomes of the simulations are between 6,000-10,000mu over the 100 year simulation period.

Figure 4.20 shows the nominal and cumulative possession hours of interventions and inspections. The bars of the stacked bar chart are regular to the 12 year frequency, as seen in Figure 4.15. As noticed in previous

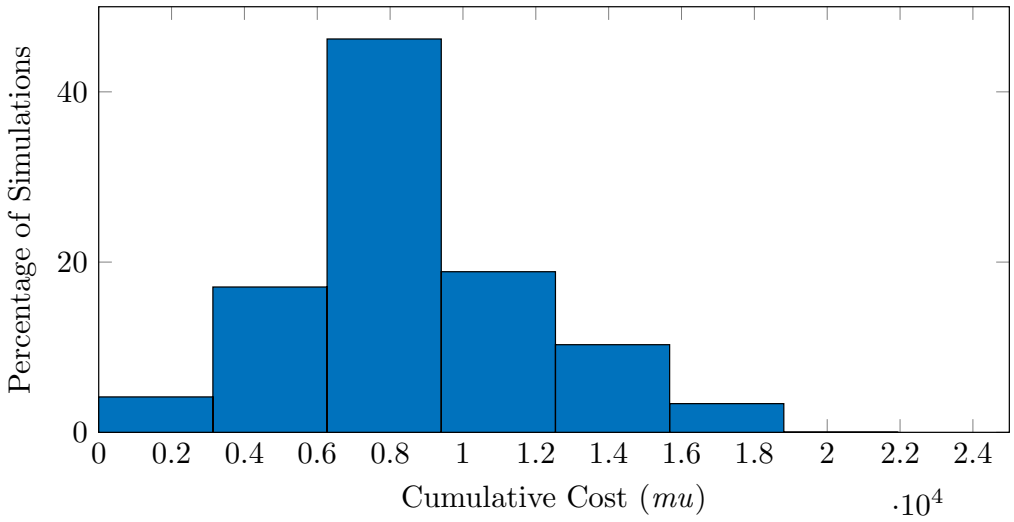


Figure 4.19: Graph to show the distribution of cumulative costs.

figures, there are smaller bars between the regular 12 year interventions which is when interventions had to be rescheduled due to the element deteriorating to a worse state requiring a return intervention. This is a useful graph for decision makers to be able to organise their workforce to perform the inspections and interventions regularly.

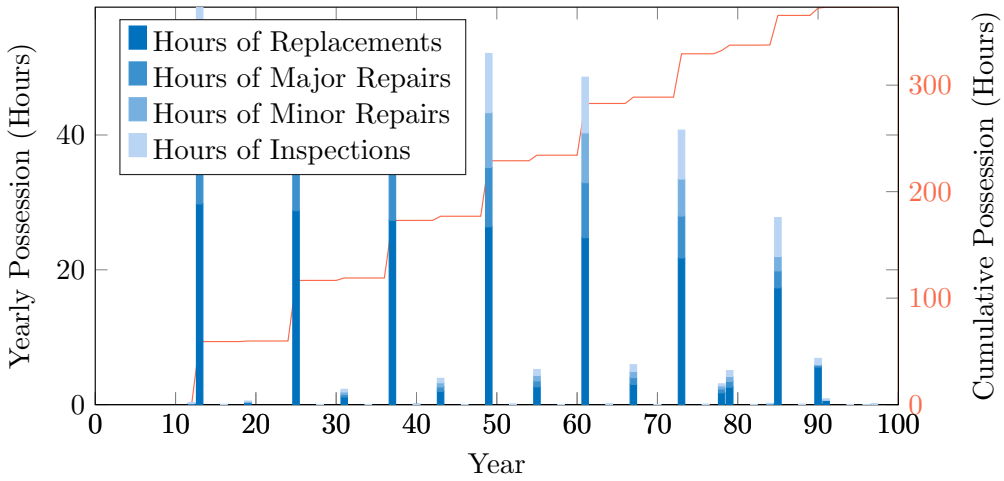


Figure 4.20: Graph to show the nominal and cumulative possession hours of interventions and inspections.

4.4 Summary of Railway Bridge Model

There are a wide variety of different systems, policies and practices that the model needs to encompass so a modelling approach that is very flexible was required. One key advantage regarding flexibility is the ability to model a changeable number of elements; adding an element is as simple as adding another token. The main focus was to strike a balance between the model being true-to-life, but not overly complicated, whilst still bringing together all the different processes that affect bridges and bridge management.

The results of the simulations show an element that starts in a new condition and is inspected and repaired according to industry guidelines. This is backed up by a significant amount of historical data which affords the model some confidence from railway bridge managers. This model can be used to run examples of bridge assets starting in any condition, with custom inspection and maintenance policies and the outputs compared. This allows bridge portfolio managers to get an estimate of when work will be required, what that work will be and the cost of that work which is invaluable knowledge when managing a portfolio of assets.

A railway bridge model has been created and calibrated with the deterioration, inspection and maintenance aspects of a typical railway bridge asset. The research now turns to investigate different factors affecting deterioration so that the model can be made more asset-specific. This should reveal more information which can be used to support decision making as well as making the model outputs more specific to individual asset groups.

Chapter 5

Local Environmental Factors (LEFs)

There have been many studies involving bridge deterioration modelling using a number of different techniques (Morcous et al., 2010; Frangopol et al., 2001; Arditi and Tokdemir, 1999; Neves and Frangopol, 2005). Many of these authors argue that there are a number of external factors that also affect bridge deterioration, but there is little research which ascertains what the factors are, how they affect the deterioration profile and how much their influence would cost to a railway structure portfolio manager.

5.1 Literature on Factors Affecting Structural Deterioration

Many studies involving bridge deterioration models hint towards the fact that there may be a multitude of different external factors affecting bridge deterioration. The problem with identifying these factors is that a significant pool of data is required to be able to conclude that there is a difference in deterioration profiles in element deterioration. The factors commonly considered include: asset age, traffic volume, span length, number of

tracks, structure type, coastal proximity and temperature variation (Morcous et al., 2002a; Niroshan et al., 2015; Patjawit and Kanok-Nukulchai, 2005).

Jiang and Sinha (1989) and Jiang (1990) conducted a study in which 5,700 highway bridges in Indiana, USA, were analysed. They created a Markov based model and analysed a number of different categories to understand the effect of different bridge attributes. For instance, the bridges were split into which highway system they were part of: "interstate highways bridges" or "other state highway bridges"; by traffic volume, interstate highways bridges was split between those which experienced less than 10,000 Average Daily Traffic (ADT) and more than 10,000 ADT; other state highways the data was split by those which experience less than 5,000 ADT, 5,000 to 10,000 ADT and those which experience more than 10,000 ADT; the climatic regions were analysed, split up into the bridges which were Northern or Southern. For each of the factors a sample set of 50 bridges was selected and used to see if the particular bridge category experienced different deterioration to the rest of the population. The results indicated that for most of the bridge subgroups, the factors being analysed were not significant enough to deviate from the standard deterioration experienced by the rest of the population. However, the results did find a statistical difference between the deterioration of interstate highways bridges and other state highway bridges. The authors concluded the analysis of the factors by stating that they will provide different performance curves for interstate highways bridges and other state highway bridges.

Scherer and Glagola (1994) studied the highway bridges in Virginia, USA. The authors explain that there are 13,000 bridges in the district and they attempt to model the deterioration process using a Markov approach. A process of grouping was performed where similar bridges were pooled together; in total 216 cases were created. The groups were decided upon a number of factors including the structure type, road network, environ-

mental condition, age of the structure and the traffic loading. The bridges were split up into which road network they were part of: interstate, urban extension and secondary. In terms of climate the data was split into: East coast, Piedmont plateau and the Western mountains. Finally, the traffic loading was split into a number of different ADT values depending on the size of the road network, ranging from 500 ADT for bridges on secondary road networks to greater than 5,000 for bridges on interstate road networks. The authors then explain the assumption that the bridges are grouped into the appropriate categories and that similar bridges in analogous conditions will have comparable performance and deterioration characteristics.

Agrawal et al. (2010) describes an approach to provide the probabilistic lifetime distributions using the Weibull distribution of 17,000 highway bridges across New York State, USA. They use case study elements to study the effects of external factors on the lifetime of the element. The examples used in the study related to the type of materials used in construction. An analysis was performed to see whether girders manufactured from steel deteriorate faster or slower than those made from weathering steel. The result of the analysis showed that elements made from weathering steel deteriorate at the same rate as standard steel elements for the first 20 years of the elements life. Beyond that point weathering steel seems to degrade slower than standard steel elements. The authors continue to analyse the difference in deterioration rates between structures with epoxy coated reinforcement bars and uncoated reinforcement bars.

Huang et al. (2010) provides a useful summary regarding all the studies in literature carried out on this topic. They state that there are a plethora of weathering factors that affect bridge deterioration. The study used inspections from 2,128 bridges in Taiwan, including traffic and weather data. The study looks at the most common types of defects for reinforced concrete and then tries to ascertain what the major and minor causes of that defect are. For instance, the author concludes that the traffic volume is a

major factor in the corrosion of the reinforcement bars. However, distance from the coast is a factor for both spalling and fragmentation. The author then groups the factors by the defect they are likely to cause; cracking seems to be the most sensitive defect as 8 of the 10 factors affect it, however honeycombing is only affected by two factors: the peak monthly rainfall and the maximum days of rain in the month. The authors concluded that the distance from the coast is one of the factors that affects bridge deterioration, but it was not one of the major factors. However, the authors also state that their population of bridges did not contain any samples that they would consider classifying as coastal assets.

Zhao and Chen (2002) performed a study regarding the causes of structural deterioration using a fuzzy logic system. A case study exercise was performed where the most critical bridge defects, cracking and spalling, were selected. The artificial intelligence system was used to find the causes of the defects. The parameters included: the structure type, bridge age and overall span length amongst others. The results suggested that cracking was highly dependant on the loading caused by traffic but the construction technique and structural design had little effect. However for spalling, the "other" factors (e.g. bridge age) had the most effect whereas loading was much less of a factor in deterioration.

In summary, a variety of literature has been evaluated. Each study used its own approach of identifying the external factors and assessing their effects. The over-riding conclusion that can be drawn from the literature is that there are a variety of external factors and they can greatly affect bridge deterioration.

5.2 Deterioration Comparison Methodology

The condition rating system used in this research is the 2-Dimensional Severity Extent Rating (SevEx) scale. As described in Section 2.2.3.7,

Network Rail (NR) already have a process of converting this from the 2-Dimensional SevEx scale to the 1-Dimensional Structure Condition Marking Index (SCMI) scale. However, this method loses the details about the defects which reduces its effectiveness at comparing deterioration profile characteristics.

Another approach was to simply use the number of condition states between inspections as a rate of deterioration e.g. an element degraded 4 condition states over 6 years and therefore degraded at a rate of 0.67 condition states/year. However, this method assumes that the difference in condition between the states is constant and equal, which may not be a valid assumption. To go from condition state B2 to B3 means that the defect has increased in extent by 5%, however to go from B2 to C2 means that the defect has evolved from light cracking to moderate cracking. Developing a conversion matrix from the 2-D SevEx system into a numerical scoring system is difficult, because weighting the conversion factors would involve expert judgement which always has a level of subjectivity.

A novel, alternative approach has been developed in this research which allows the states to remain in their 2-D SevEx form and be independent of one another. No conversion factors are applied which means that there is no ambiguity about the weightings or subjectivity. The way this works in practice is to match the elements to their corresponding attribute e.g. their proximity to the coast. Then split the dataset according to the attribute in use, e.g. elements within 20km of the coast. Once the data has been split into the number of categories required, the element inspections are processed into a matrix of occurrences. This provides an indication of how the defects evolve over time. From the occurrences, a matrix of Mean Time to Failure (MTTF) times can be calculated. The "distance" between nodes is the MTTF. The MTTF is calculated using historic inspection data and is explained in more detail in Section 4.2.4.

The higher the probability of an element taking a particular route,

the lower the MTTF value, and in turn, a higher failure rate. Therefore, it was most appropriate to calculate the distances using the shortest path method, as it coincides with the most likely used route. Dijkstra's algorithm (Dijkstra, 1959) was used to calculate the shortest path between nodes. In this research, the shortest path will reveal the most likely route from one condition state to another and the shortest path MTTF value between the two states. Failure in this context is defined as reaching the destination node. An example of a network diagram is shown in Figure 5.1. A subset of conditions, A1 to D4 are shown, along with the possible paths and the path distances. The path distances are the MTTF times, calculated in years. The shortest path is shown in the solid line.

The network analysis approach has been used to find the MTTF times between various thresholds. Namely, the time it takes to get from a certain condition state to the states associated with the Major Repair and Replacement thresholds. The Minor Repair threshold was not considered because it begins at condition state B2 and therefore only state A1 would be considered. The thresholds are back-converted from NR guidelines as shown in Table 4.7. The MTTF times to get to these thresholds are used as a comparison to ascertain if a Local Environmental Factor (LEF) is playing a factor in the deterioration of the element.

This approach allows the assessment of the influence of a large set of environmental conditions with limited computational cost. The approach assumes that the evolution between a chosen condition state and the condition states relating to an intervention threshold, can be characterised by the duration of the critical path (i.e. the path with minimum duration). The approach is a simplification as multiple paths exist connecting the states, however, the results show that the shortest path was usually significantly shorter than any competing path. As this method was only used to identify which environmental factors should be investigated further and a more detailed approach was used to calibrate the model parameters (see

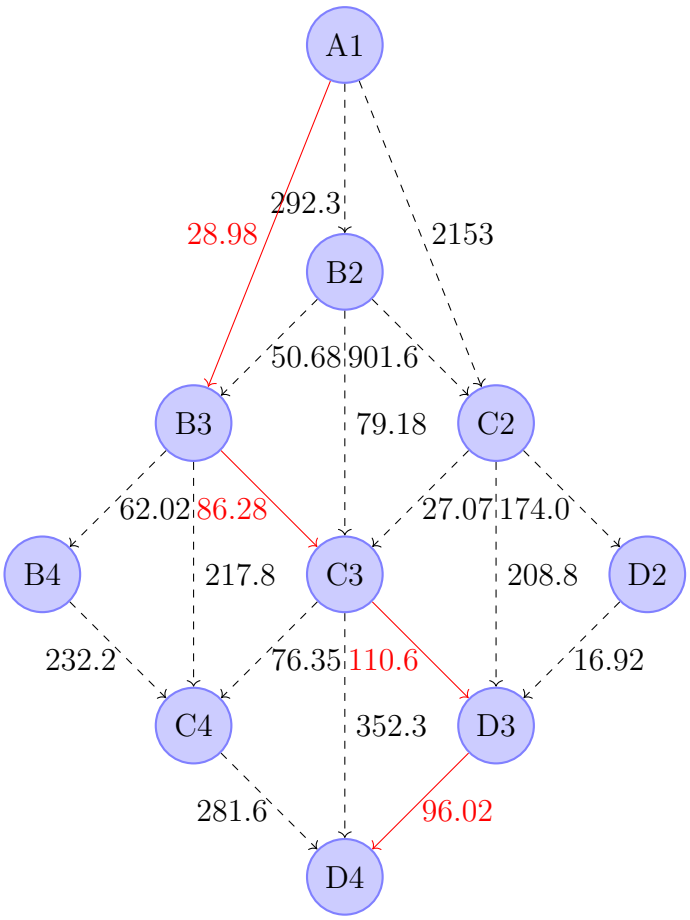


Figure 5.1: Network map showing a subset of the condition states and example MTTF times between each state. The shortest path from A1 to D4 is shown by a solid line.

Section 4.2.4.1), the errors introduced were deemed to be acceptable.

5.3 Local Environmental Factor (LEF) Analysis

5.3.1 Methodology

The approach used to analyse the impact of the LEFs includes both a graphical and statistical analysis. The MTTFs from each condition state to the Repair and Replacement thresholds are used to evaluate if there

is any evidence that the attributes should be compared separately. To aid in the decision making process, some of the MTTF graphs have been re-ordered because the graph axes are linear, however they represent movement through a 2-D system. Deterioration profiles for the different groups of bridges were produced and assigned to the Deterioration Module of the Petri-Net (PN) model. Simulations were then carried out with the model on a typical bridge element in each LEF category. A statistical Analysis of Variance (ANOVA) test was used on the model outputs to confirm that the deterioration factors were indeed statistically different. This approach was decided upon because it verifies and confirms if deterioration rates would be statistically different among different groups of bridges.

5.3.1.1 Structure Type

Railway bridge assets are designed in a number of configurations. The vast majority of the assets fall into the structure types "Overline bridge" and "Underline bridge". There are other structure types e.g. "side of line bridge", however the vast majority of bridges (94.4%) are either underline or overline bridges. Overline bridges are built for the roadway to go over the structure and the railway to go beneath the structure; in this design the structural loading will be dominated by the roadway. Underline bridges are built for the railway to go over the structure and the roadway to go beneath the structure; in this design the structural loading will be dominated by the railway. Underline and overline bridges are subjected to different structural loading due to their configurations. Therefore, an analysis was performed to ascertain if there is a difference in the way that these types of bridges deteriorate.

Figure 5.2 shows the results of MTTF values between overline and underline bridges to the Major repair threshold. This graph shows the MTTF from a range of starting conditions to the Major Repair threshold. The graph is used to identify if there is enough evidence to consider the at-

tributes as significant or not. In general, however, the overline bridges seem to have higher MTTF values, suggesting they take more time to get from one state to another and therefore slower deterioration. The likelihood is that underline bridges will be subjected to higher loading considering they take the railway over a roadway. Therefore, the structural loading will be higher, leading to more cracking, for instance, and subsequently quicker rates of deterioration. The results of the analysis suggest that underline and overline bridges deteriorate at different rates and should be considered separately henceforth.

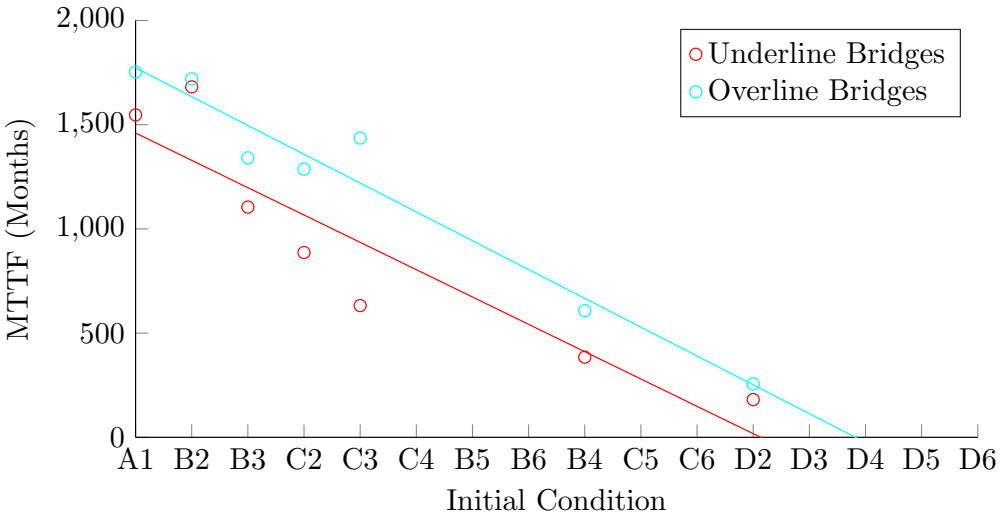


Figure 5.2: Difference in MTTF times of Underline bridges and Overline bridges to get to the Major Repair threshold.

5.3.1.2 Traffic Loading

Considering a difference in structure type has been determined, an analysis was carried out to see if structural loading of underline bridges was important as a deterioration factor. The premise was that the more loading the bridge was subjected to, the more severe the defects would be and therefore the faster the deterioration. Each underline bridge was cross-referenced against track location. Track data was obtained which details the total

amount of Equivalent Million Gross Tonnes Per Annum (EMGTPA) which passes over each section of the line. This is calculated by the total amount of tonnage going over the track where each train is multiplied by factors depending on its wear characteristics. A number of factors impact the load and wear factors including: the percentage of freight on the train, the power of the tractive unit and the maximum speed of the train (Network Rail, 2011).

The bridges have been grouped into those which experience less than 3.5 EMGTPA, those which are subjected to between 3.5 EMGTPA and 12 EMGTPA and finally, those which experience the most severe loading at over 12 EMGTPA. The group boundaries were decided upon simply to make the sample sizes as equal as possible, in accordance with statistical conformity. The results of the analysis can be seen in Figure 5.3. The data points and trend lines are grouped by colour to indicate the MTTF values for the same set of data to two different thresholds: Major Repair and Replacement. The data points and trend lines grouped towards the bottom are to show the MTTF values to Major Repair. The data points and trend lines grouped towards the top are to show the MTTF values to Replacement.

The MTTF values presented in Figure 5.3 suggest that there is no discernible different in deterioration rates depending on the EMGTPA. Upon reflection, the study is focusing on concrete structures which are relatively recent in bridge construction and therefore would have been built to modern standards (British Standards/Eurocode). In the Eurocode legislation for construction, each element is designed with consistent safety factors (European Committee for Standardization (CEN), 1996) and therefore, the capacity of a concrete bridge is such that any of the EMGTPAs tested is within specification.

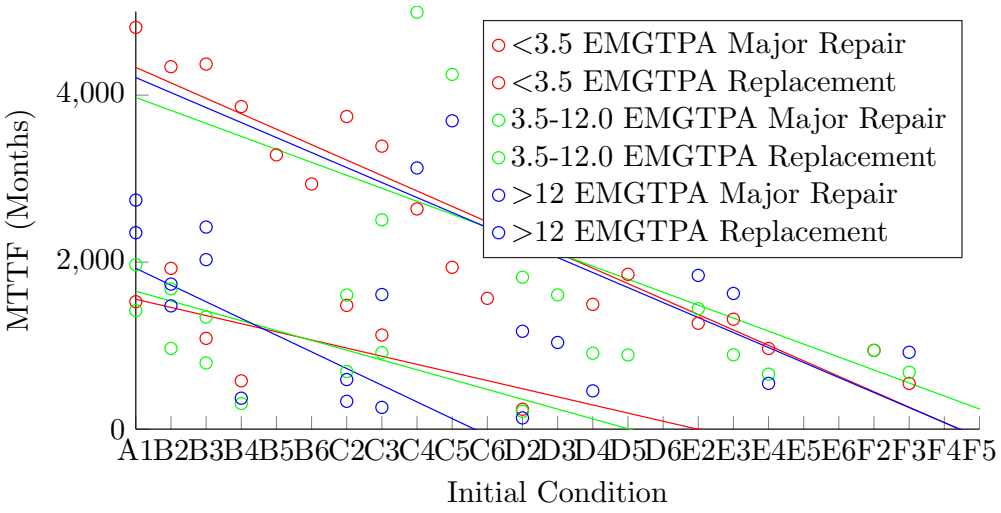


Figure 5.3: Difference in MTTF times of Underline bridges under different loading conditions to get to the Major Repair and Replacement thresholds.

5.3.1.3 Maximum Line Speed

Another LEF that is complementary to traffic loading is train speed. The proposition for this analysis was that faster trains cause larger dynamic amplification factors. The way the analysis was carried out was that the underline bridge locations were cross-referenced with track data to determine the maximum line speed of the track. Each section of track is categorised with a maximum line speed to the nearest five Miles Per Hour (MPH). Groupings of these line speeds were performed using data from the line speed database.

The track has been grouped from those which experience very slow traffic (0-40 MPH); those which experience a low-medium traffic speed (40-75 MPH); a medium-high traffic speed (75-100 MPH) and those which are on high speed lines (100-130 MPH). The results of the analysis can be seen in Figure 5.4. Again, the data has been grouped by colour to show the same data set with the Major Repair and Replacement thresholds.

The results of Figure 5.4 suggests that there is no correlation between bridge deterioration and line speed. It seems that different track speeds are categorised as different route criticalities meaning they are subjected

to different inspection and maintenance procedures as well as design requirements. This may mean that faster lines are inspected more often and therefore bridge defects may be picked up in the process.

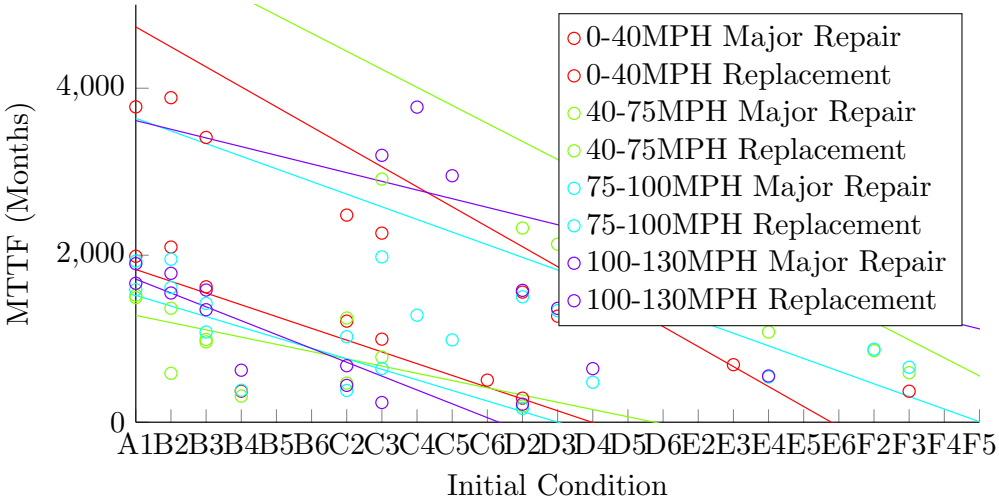


Figure 5.4: Difference in MTTF times of Underline bridges with different track speeds to get to the Major Repair threshold.

5.3.1.4 Galvanic Response

The main mechanism of concrete structure deterioration is spalling, caused by the corrosion of the reinforcement bars that make up reinforced concrete. As the reinforcement bars corrode, they expand, pushing out the cover layer of concrete, further exposing the reinforcement bars. It follows that environmental conditions that cause accelerated corrosion in metals should also affect reinforced concrete due to its reliance on the reinforcement bars. Data is available to show the galvanic response in different areas of the UK (UK Galvanizers Association, UK Galvanizers and High Chemicals UK Ltd., 2002). In each 10km^2 across the UK a corrosion rate was calculated for zinc, a popular galvanising material. Galvanic corrosion is a combination of factors including temperature fluctuations, salinity, pollution levels and humidity (Varela et al., 1997; Hack, 1988). These corrosion rates vary from 0.5-2.5 μ m/year. Reinforcement bars in reinforced concrete are not made

from zinc, but from steel and so corrosion ranks were used instead, ranging from 1-5 i.e. corrosion rate 0.5μ m/year became corrosion rank 1; corrosion rate 2.5μ m/year became corrosion rank 5. Figure 5.5 shows the map of the UK overlaid with the galvanic response information.

The bridge locations were cross referenced with the galvanic response map and then grouped according to their corrosion rank. There were no bridges to be found in areas relating to corrosion rank 1 so it was disregarded. There were a minimal amount of bridges in areas subjected to corrosion rank 2 so it was grouped together with corrosion rank 3, which covered a much larger group of bridges.

The results of the analysis can be seen in Figure 5.6. Looking at the trend lines, it is quite evident that the corrosion levels should be considered separately. Corrosion rank 2/3 seems to have quite high MTTF values with a strong slope on the trend line. This suggests that bridges in areas of corrosion rank 2/3 seem to have higher MTTF values, relating to longer times between states and therefore slower deterioration. This would follow with expectation as a lower corrosion level would intuitively relate to slower deterioration. Similarly, corrosion rank 4 seems to trend below corrosion rank 2/3 relating to lower MTTF values, faster movement between states and therefore more severe deterioration. Finally, corrosion rank 5 seems to have the most severe deterioration. All of the MTTF values are comparatively low and the slope on the trend line is minimal suggesting that the corrosive nature of the area is such that a bridge in any condition will suffer greatly from the environment. This is in line with what is expected as corrosion rank 5 is only in places with extreme fluctuations in temperature, humidity and salinity (see Figure 5.5). Overall the results of the galvanic response analysis suggest that there are significant differences in bridge deterioration relating to the area of galvanic response they are situated in. Henceforth, they should be treated separately when considering the rate of deterioration.

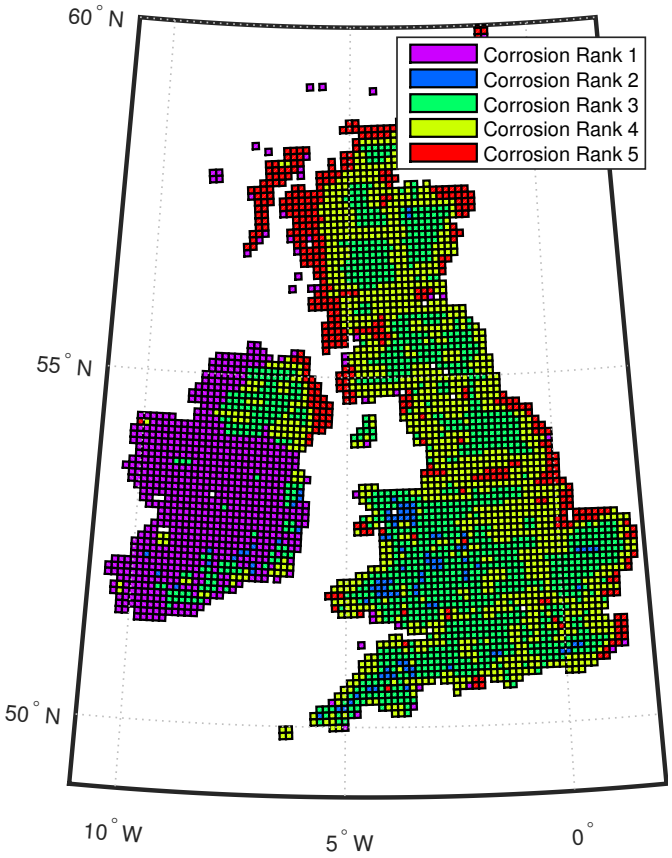


Figure 5.5: Different corrosion ranks in the UK (UK Galvanizers Association, UK Galvanizers and High Chemicals UK Ltd., 2002)

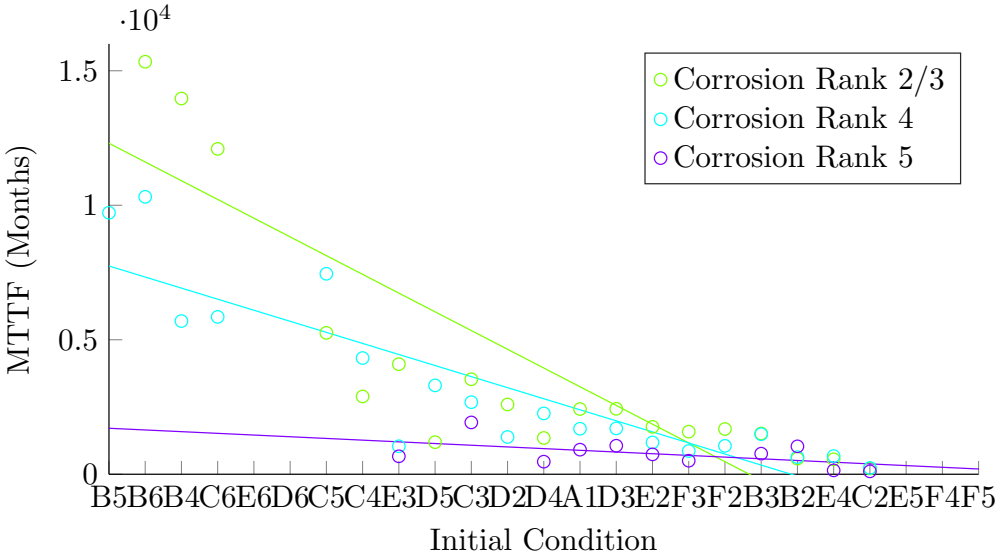


Figure 5.6: Differences in MTTF times for bridges in different areas of galvanic response to the replacement threshold.

5.3.1.5 Maximum Temperature

Data provided from the Met Office and Amey was used to analyse the mean maximum temperature which the asset would be exposed to. The mean maximum temperature is the mean of the maximum air temperatures recorded each day in the year. This was calculated by triangulating the mean maximum temperature between the nearest weather monitoring stations to the asset. The reason that this is important is that chemical processes are accelerated at higher temperatures (Lai, 1990). Therefore, it is possible that rusting of metal elements and chloride penetration in concrete elements may also be accelerated. This would be evident in the rate of deterioration between elements in different temperature regions.

To get equal groups of data within each of the categories, quantiles were used to calculate the temperature ranges. These were calculated as elements which were subjected to maximum temperatures of 19 °C, elements which are subjected to maximum temperatures between 19 °C and 21 °C and those which experience maximum temperatures of over 21 °C.

Figure 5.7 shows the results of the analysis. The expected result would be to see faster deterioration with higher maximum temperatures, however the results do not seem to agree with this. The results do not seem to correlate and so maximum temperature has been discounted as a factor affecting deterioration. It is possible that the mean yearly temperature may provide more insight, however this data was not available.

5.3.1.6 Coastal Proximity

To analyse the effect of coastal proximity each of the structures with coordinates needed to be cross-referenced to a coastline map. A Global Self-consistent, Hierarchical, High-resolution Shorelines (GSHHS) database was used to plot the coastline and the coordinates of each bridge used to calculate the proximity of the bridge to the coast (National Oceanic and

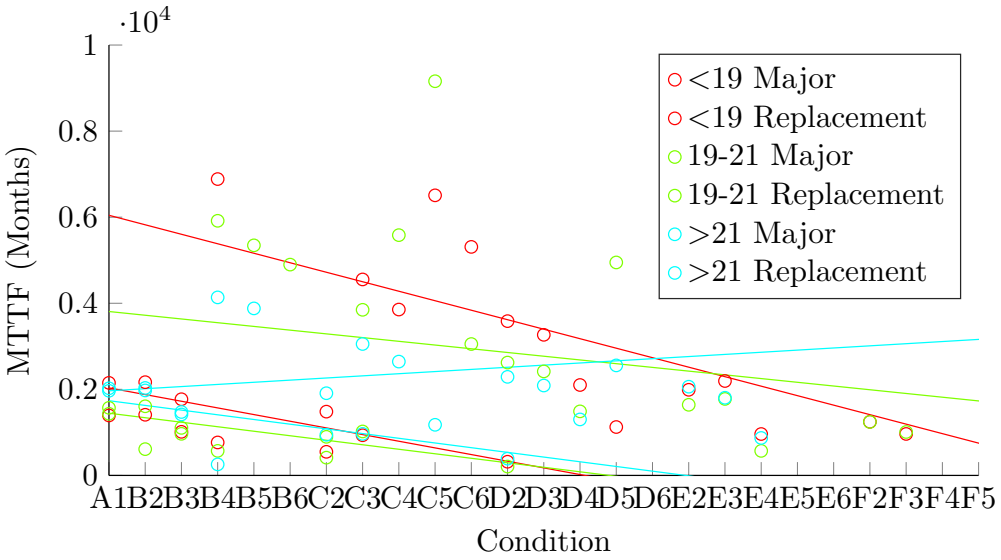


Figure 5.7: Difference in MTTF times of bridge elements subjected to different maximum temperatures (given in degrees Celsius) to the Major Repair and Replacement thresholds.

Atmospheric Administration (NOAA), 2015). The bridges proximity was then aligned with its corresponding element inspections. This allowed the inspection data to be split at various distances and the coastal bridges compared with the inland bridges. The distance was varied from 0.5km to 30km to ascertain the difference in MTTF analysis between the coastal and inland bridges.

Figure 5.8 shows the results of the analysis with the MTTF values. These are the mean expected times for a bridge to deteriorate from a new (A1) condition to a state requiring Minor Intervention (see Table 4.7). The graph has been normalised with the inland MTTF values set at 1. What is evident is that the coastal bridges, at every position, have lower MTTF values suggesting that they move more quickly between condition states and therefore deteriorate faster. For the Major Intervention threshold, it can be seen that coastal bridges on average deteriorate roughly 35% faster than inland bridges. Additionally, it seems that bridges closer than 5km to the coast deteriorate even faster.

Figure 5.9 shows the results of the analysis relative to the Replacement threshold (see Table 4.7). Again, the graph has been normalised so that the inland bridges have MTTF values set at 1. What is clear is that the coastal MTTF values are always lower than inland bridges, with MTTF values being around 30% lower for coastal bridges. The bridges closer than 5km do not seem to be as affected as in the Figure 5.8. This may be because the saline atmosphere accelerates chloride penetration into concrete which is the precursor to spalling. Once spalling has begun, the surface concrete often falls off which directly exposes the reinforcement to corrosion. Therefore at less severe condition states, where cracking and spalling are just developing, the coastal environment is more significant. Additionally, it seems that beyond 25km the MTTF values seem to consolidate between coastal and inland bridges suggesting that the effect of the coastal environment is coming to an end.

Overall, it can be seen that there is a distinct difference between coastal and inland bridge deterioration. This means that they should be treated as distinct groups. The most intuitive way to group the data is those bridges which are adjacent to the coast and the most affected (<5km), the bridges which are moderately affected by the coastal environment (5-25km) and the inland bridges which are beyond the effect of the coastal environment (>25km).

Expert opinion indicates this large disparity in deterioration rates may be because of the direct exposure to the saline atmosphere, accelerating their deterioration. It is recognised that the proximity to the coast is an estimator of the chloride concentration which is, most likely, the parameter causing the increased rate of deterioration. The classification should most likely include the average wind velocity and predominant wind direction from the coastline. The absence of this data prevented any further developments at this stage.

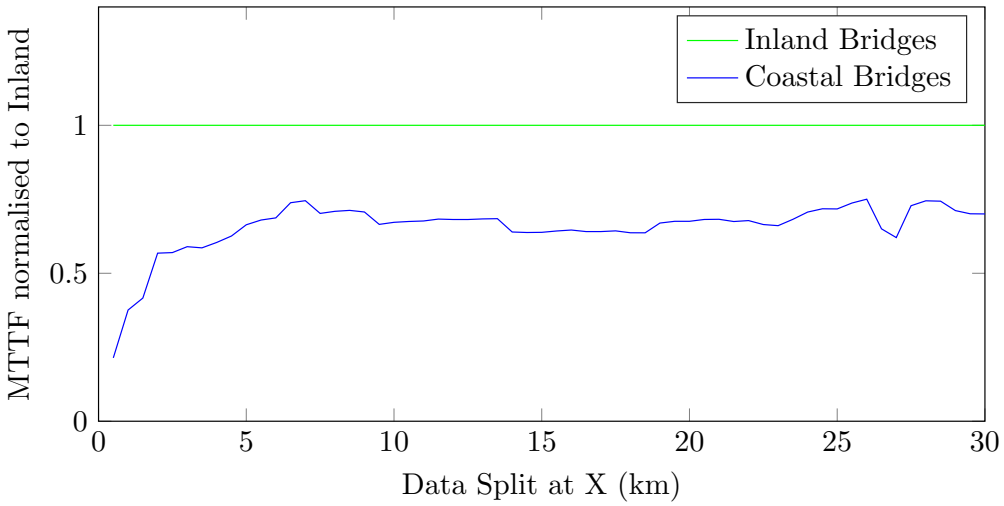


Figure 5.8: Relative MTTF of coastal and inland bridges from a new (A1) condition to the Major Intervention threshold.

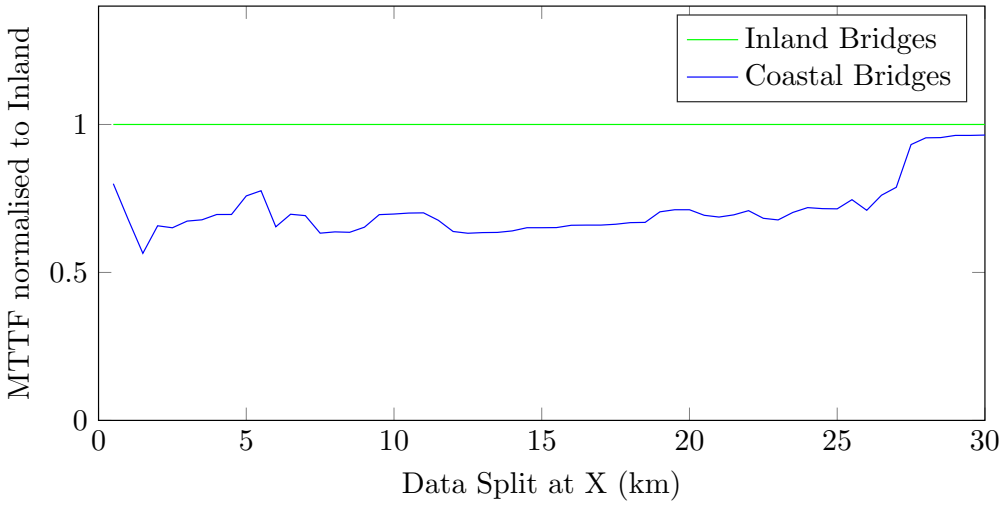


Figure 5.9: Relative MTTF of coastal and inland bridges from a new (A1) condition to the Replacement threshold.

5.3.1.7 Frost Days

Assets exposed to saline environments are also of concern. Often in the UK, when frost is expected, the local authority will spread salt on the roadways to try to reduce the chance of road accidents. Salt is an accelerator of rusting and increases chloride penetration in concrete elements. An analysis was carried out to see if there was any correlation between the rate of deterioration of bridge elements and the number of frost days the elements would be subjected to. For this analysis the data provided from the Met Office and Amey was used.

The data has been grouped into those which experience fewer than 39 frost days per year, those which experience between 39 and 48 frost days per year and those which experience greater than 48 frost days per year. The ranges were chosen to make the population sizes equal.

Figure 5.10 shows the results of the analysis. The results show that to reach the Major Repair threshold, the number of frost days is not a significant factor affecting deterioration. This can be seen because the data points are scattered in the same region. When considering the Replacement threshold, the groups are more clear, but do not follow a logical order. It can be seen that the elements subjected to 39 frost days or less have the highest MTTFs. However, the elements which are subjected to more than 48 frost days per year seem to have middling MTTFs and the elements which have between 39 and 48 frost days have the quickest MTTFs. When considering both the results from the Major Repair and Replacement thresholds, there is no evidence to say that the number of frost days is a factor affecting bridge deterioration.

Upon further discussion with industry experts, the increased levels of chloride concentration which occur after salt spreading are temporary and the salt normally washed away by natural precipitation within a few days. The short-term peaks of chloride concentration are assumed not to be as

significant to structural deterioration as long-term chloride penetration, as would be experienced by close proximity to the coast.

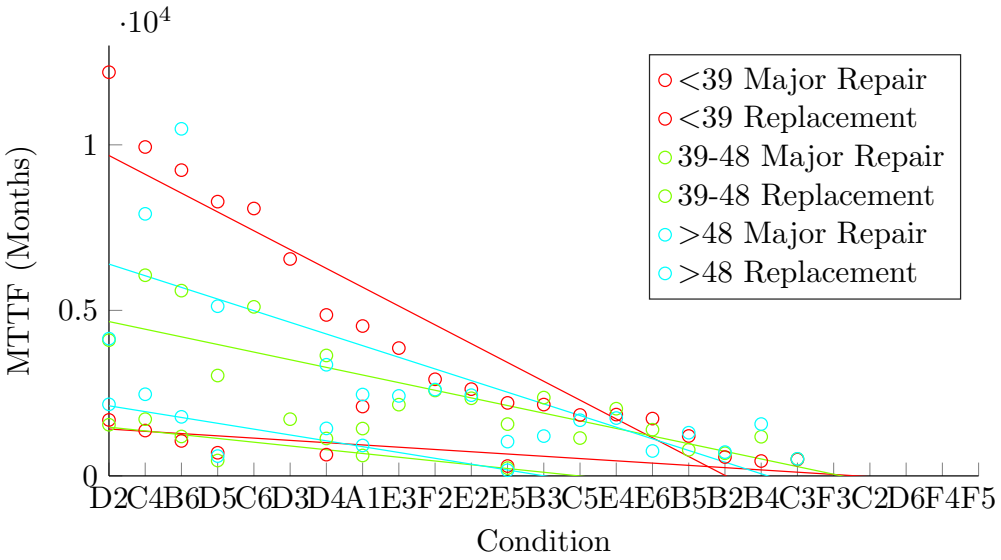


Figure 5.10: Difference in MTTF times of bridge elements subjected to different numbers of frost days to the Major Repair and Replacement thresholds.

5.3.1.8 Rainfall

Considering the effect of corrosion on metal in both metallic elements and the reinforcement bars in concrete elements, the amount of rainfall could also be a factor affecting deterioration. Weather data provided by the Met Office and Amey was used for the analysis. The amount of rainfall, in millimetres, was recorded at each weather station. The rainfall data and proximity to the asset was used to calculate the rainfall which would have been experienced by the asset. This could then be analysed to see if there was correlation between the rate of deterioration of bridge assets and the average amount of rainfall the element is subjected to yearly.

The elements were grouped into those which experienced less than 635mm of rainfall per year on average, those which experienced between 635 and 775mm of rainfall per year on average and those which experi-

enced more then 775mm of rainfall per year on average. Figure 5.11 shows the results of the analysis. When looking at both the Major Repair and Replacement thresholds, no correlation is evident. Therefore, from this analysis, it does not seem that the amount of rainfall is a factor affecting deterioration.

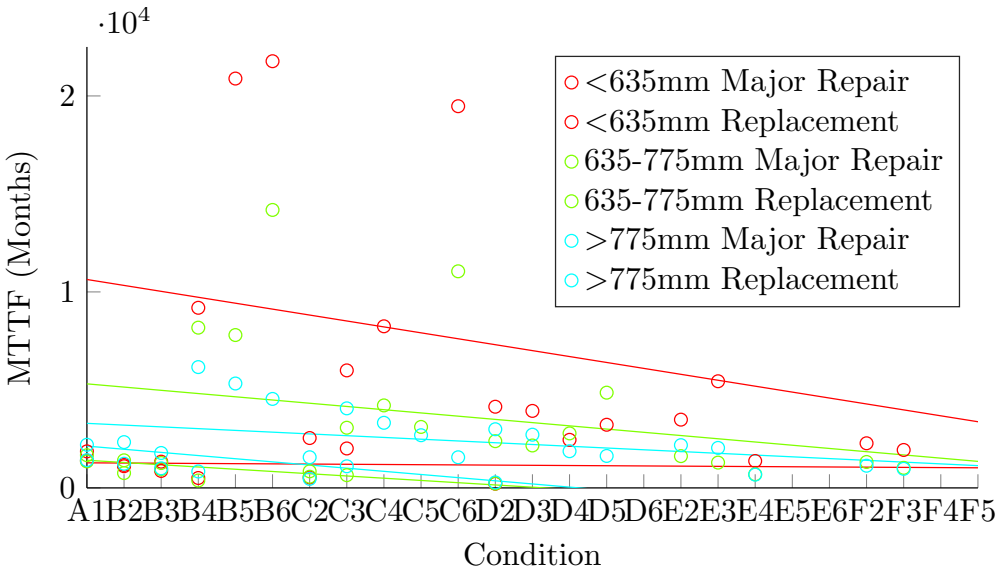


Figure 5.11: Difference in MTTF times of bridge elements subjected to different amounts fo rainfall to the Major Repair and Replacement thresholds.

5.3.1.9 Summary

A number of different LEFs have been analysed. Starting with the structure type, it was clear to see that overline bridges and underline bridges should be analysed separately. Underline bridges, where the railway is carried over the roadway, was seen as the most critical structure type. So analysis was done to see whether traffic loading on underline bridges played a significant role in the bridges deterioration. The analysis showed that there is no significant difference. A complementary analysis was undertaken into the track speed of underline bridges. Again, this provided no significant differences in bridge deterioration between the line speeds of

underline bridges. The next factor to be analysed was galvanic response. A comprehensive map of the galvanic response rate in different areas of the UK was used and compared against bridge deterioration. The results gave a positive result showing there is indeed a difference in bridge deterioration when grouped by the different corrosion ranks. Considering the results of the Galvanic Corrosion, a complimentary analysis was carried out into the yearly temperature which the bridge assets are subjected to. This study is complimentary because chemical reactions are often accelerated by increased temperatures. Unfortunately, there did not seem to be any correlation between the element temperature and the deterioration rate. Another factor to be investigated was the effect of coastal environments on bridge deterioration. The results showed that there is a significant effect on bridge deterioration, bridges which are very close to the coast (<5km) are the most severely affected, and even those up to 25km are affected. There was some discussion to see whether the galvanic response study was correlated to the coastal proximity study. When looking at Figure 5.5 it is clear that the corrosion ranks are not simply a correlation of coastal proximity. Bridges that are within 5km of the coast can be in corrosion rank 2, 3, 4 or 5. Galvanic corrosion can be affected by many more factors than salinity (e.g. temperature fluctuations, pollution levels and humidity (Varela et al., 1997; Hack, 1988)). Therefore galvanic response should be considered as a separate attribute. Considering the results of the Coastal Proximity, a complimentary study into the number of frost days was carried out. The link between them is the saline environment created by the road salt that is spread to avoid road accidents; the greater number of frost days, the more salt would be spread on the bridge asset. The results of the analysis, however, did not provide evidence of a link between the number of frost days and the rate of deterioration. Finally, the average amount of rainfall per year was analysed to see if it had an effect on element deterioration. The results of this analysis did not show any correlation and so rainfall was

not deemed to be one of the factors affecting deterioration.

The factors which have been determined as critical to bridge deterioration in this research are: structure type, galvanic response and coastal proximity. It was found in Section 5.1 that Scherer and Glagola (1994) and Zhao and Chen (2002) had identified the structure type as a factor affecting deterioration. Even though this was both classified and analysed differently in this study, the results were in agreement. Huang et al. (2010) identified that the coastal proximity had an effect on fragmentation and spalling of reinforced concrete; the authors identified this as a minor factor. The results of this study identified coastal proximity as a factor of major importance, second only to galvanic response. Table 5.1 shows the total numbers of concrete bridge girder elements when grouped by the LEF scenarios. Section C.1 contains all the detailed MTTF outputs from the analyses.

Table 5.1: The number of main girder elements in each category.

		Proximity To Coast			
Structure Type	Corrosion Rank	<5Km	5-25Km	>25Km	Total
Overline Bridges	2,3	1797	2062	14503	18362
	4	3347	4786	14110	22243
	5	394	316	2420	3130
Underline Bridges	2,3	1471	3524	8977	13972
	4	2024	2962	8962	13948
	5	1190	386	1171	2747
	Total	10223	14036	50143	74402

5.4 Incorporating Local Environmental Factors (LEFs) into the Railway Bridge Model

Each LEF category relates to a different deterioration profile; each LEF deterioration profile is embedded into the transitions of the Deterioration

Module. A sample bridge element has been simulated subjected to each of the LEFs. The results of each of the scenario simulations can be found in Table 5.2. The results detail the probability of different maintenance requirements over the 100 year simulation period. The elements begin the simulation in condition state A1 (new condition). The baseline scenario (ID 1) contains all the available data and it can be seen that on average, over the 100 year simulation, 57% of the time the element was in a condition that would only require Minor Repair. At the 50 year time step, the probability of the element being in a condition that would only require Minor Repair was 56%. Over time, the probability the element is in a condition which would only require Minor Repair reduces, and the probability of requiring a Major Repair or Replacement increase. This is further evident at the 100 year time step where the probability of the element being in a condition that would only require Minor Repair was 1%, whereas the probability of the element being in a condition that would require Major Repair was 87% and the probability of the element being in a condition that would require Replacement was 11%.

When comparing structure types (ID 2,3) it can be seen that overline bridges seem to fare better as they spend 67% of the time in a condition state only requiring Minor Repair. Underline bridges perform similarly to the baseline condition with 58% of the time in a condition state only requiring Minor Repair. Note that ID 1 contains all the available data, however not all of this data is in ID 2 and 3 because not all bridges are underline or overline bridges, hence the disparity in the probabilities. However, all the bridges in ID 4, 5 and 6 are in ID 1; and similarly all the bridges in ID 7, 8 and 9 are in ID 1.

When looking at coastal proximity (ID 4,5,6) the bridges closest to the sea seem to degrade the fastest, spending only 48% of the time in a state only requiring Minor Repair. Those which are 5-25Km seem to fare slightly better, but those which are inland (>25km) seem to fare the best with 71%,

higher than the baseline scenario.

Finally, galvanic corrosion scenarios (ID 7,8,9) are most interesting as they have the most variation. Those in low corrosion areas spend almost 73% of their time in a state only requiring Minor Repair, even better than inland bridges. The bridges that are in corrosion rank 4 spend 67% of their time in a state only requiring Minor Repair. Finally, bridges that are in the most corrosive areas (ID 9) spend only 40% of their time in a state only requiring Minor Repair, which is even lower than those <5km from the coast. These results suggest that structural deterioration is heavily dependant upon the LEFs.

Table 5.2: Results of the deterioration module simulation for each of the scenarios.

				Probability						
				Average	At 50 years			At 100 years		
ID	Structure Type	Coastal Proximity (km)	Corrosion	State Requiring Minor Repair	State Requiring Minor Repair	State Requiring Major Repair	State Requiring Replacement	State Requiring Minor Repair	State Requiring Major Repair	State Requiring Replacement
1	All	0 - Inf	2,3,4,5	0.5714	0.5561	0.4367	0.0071	0.0109	0.8741	0.1149
2	Overline Bridges	0 - Inf	2,3,4,5	0.6708	0.6947	0.3020	0.0033	0.0156	0.9215	0.0629
3	Underline Bridges	0 - Inf	2,3,4,5	0.5823	0.5791	0.4119	0.0090	0.0095	0.8676	0.1229
4	All	<5	2,3,4,5	0.4830	0.4428	0.5482	0.0089	0.0064	0.8888	0.1048
5	All	5-25	2,3,4,5	0.4944	0.4507	0.5306	0.0187	0.0121	0.8004	0.1875
6	All	>25	2,3,4,5	0.7121	0.7371	0.2572	0.0057	0.0339	0.8598	0.1063
7	All	0 - Inf	2,3	0.7251	0.7461	0.2472	0.0066	0.0202	0.8878	0.0921
8	All	0 - Inf	4	0.6750	0.6947	0.2967	0.0086	0.0340	0.8564	0.1096
9	All	0 - Inf	5	0.4038	0.2949	0.6449	0.0602	0.0025	0.6549	0.3425

5.4.1 Local Environmental Factor (LEF) ANOVA Analysis

An ANOVA test was deemed most suitable to determine if the observed deterioration trends identified in Section 5.3 are correct and significant differences exist in deterioration rates amongst different LEFs. To perform this test, each of the LEF deterioration profiles were embedded into the PN model. The model outputs were then compared to see if they are statistically different. This approach was decided upon as the models are targeted for use as a decision support tool so it was most important to test the model itself. Each of the model instances were simulated using 5,000 samples and the cost outputs were compared to see whether the categories within each LEF are indeed statistically different e.g. underline and overline bridges within the structure type category. This was carried out at the 99% confidence interval. The P-value returned from the ANOVA test reveals if the factors were statistically different.

Table 5.3: Extract of ANOVA analysis results comparing the categories within each factor. The test was carried out at the 99% confidence interval.

Factor	Structure Type	Coastal Proximity	Galvanic Response	Traffic Loading
Categories	2	3	3	3
P-Value	6.04×10^{-47}	8.67×10^{-185}	$<2.25\times10^{-308}$	0.461

An extract of the results of the analysis are summarised in Table 5.3. When comparing the categories within Structure type, Coastal Proximity and Galvanic response to each other, the resulting P-Values are less than the significance level of 0.01. This indicates that the categories are statistically different indicating that their deterioration profiles differ. Factors which were not found to be statistically different had P-values above the significance level of 0.01 e.g. traffic loading. These results concur with the conclusions drawn from section 5.3.1.9.

5.5 Local Environmental Factors (LEFs) Graphical Model Outputs

When simulating the PN model, each of the LEFs scenarios can be compared. The impact of each LEF scenario can be measured and compared in terms of the Whole Life-Cycle Costing (WLCC). In addition, by simulating the LEF scenarios in the PN model, it is possible to see the knock-on effects that the LEFs create. The most sensible approach to comparing the scenarios is to use a like-for-like approach so that the outputs can be compared to one another. The scenarios were simulated in the PN model with a "Managed" maintenance strategy. This means that the elements were only repaired when they required Major repair or Replacement; Minor repairs were not considered. The elements begin the simulation in condition state A1, like new condition. Additionally, in the original model, inspections of structures depends on the condition of the structure. The better condition a structure is in, the less frequently the inspections are scheduled. For structures in poorer condition, they need to be monitored more closely and so the inspection frequency is closer together. However, for the scenario comparison, the inspections were fixed at every 3 years so that there is no bias. Each scenario was run with a single concrete girder element, the exemplar element in this research. The results of the scenario simulations can be seen in Table 5.4.

ID 1 is the baseline scenario and it contains all of the available data. It can be seen that the mean cumulative cost of maintenance over the 100 year simulation period was 7,900mu. Overline bridges (ID 2), where the roadway travels over the railway, experiences fewer maintenance actions and therefore a lower mean cumulative cost of 3,600mu. In contrast, underline bridges (ID 3), seem to have many more maintenance actions and the mean cumulative cost is almost twice as much as if the element were on an overline bridge. These results show there is a significant difference

Table 5.4: Cumulative cost results of scenario simulation.

ID	Structure Type	Coastal Proximity (km)	Corrosion Rank	Cumulative Cost (nearest $100mu$)	Relative Cost to ID 1
1	All	0 - Inf	2,3,4,5	7,900	1.000
2	Overline Bridges	0 - Inf	2,3,4,5	3,600	0.460
3	Underline Bridges	0 - Inf	2,3,4,5	7,100	0.906
4	All	<5	2,3,4,5	15,100	1.918
5	All	5-25	2,3,4,5	13,700	1.736
6	All	>25	2,3,4,5	2,800	0.355
7	All	0 - Inf	2,3	1,800	0.235
8	All	0 - Inf	4	4,000	0.512
9	All	0 - Inf	5	27,500	3.501

in how underline and overline bridges should be managed.

When looking at the effects of coastal proximity (ID 4,5,6), it can be seen that elements that reside on bridges closer than 5km to the coast experience faster deterioration with mean cumulative costs of 15,100mu. This is almost double what the baseline scenario costs which shows that coastal proximity should play a pivotal role in the management of railway structures. Similarly, elements on bridges between 5-25km from the coast do not fare much better with mean cumulative costs of 13,700mu. Lastly, elements on bridges that are far from the coast (>25km) seem to deteriorate the slowest, requiring the least amount of maintenance as their mean cumulative costs are only 2,800mu.

Finally, the effects of galvanic response (ID 7,8,9) seem to be quite influential. Elements on bridges in areas of low corrosion seem to deteriorate slowly, requiring little maintenance as their mean cumulative cost only amounts to 1,800mu, only a quarter of the baseline scenario. In stark contrast, however, elements on bridges in an area of high galvanic response (ID 9) seem to deteriorate very rapidly, requiring the most maintenance of all the tested scenarios. The mean cumulative cost amounts to 27,500mu which is more then triple the cost of the baseline scenario. This shows a

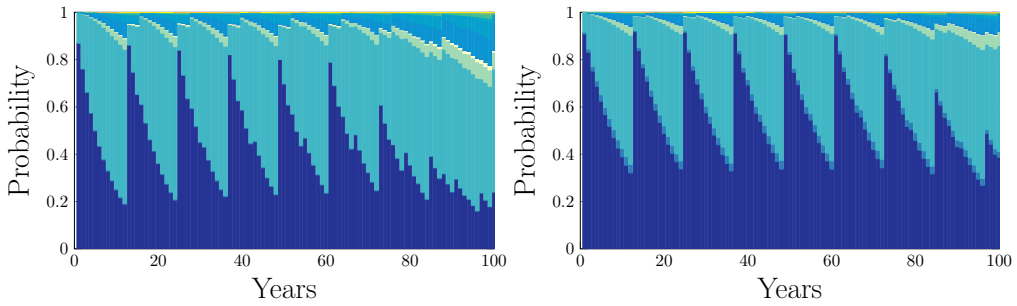
significant difference in maintenance costs over the simulation period. The results can be used to determine which LEFs are more dominant than others. Table 5.5 shows which LEF would be dominant where bridge elements are exposed to more than one LEF. For example, a bridge element which is both <5Km from the coast (ID4) and in an area of low corrosion (ID7) would experience the worse deterioration of those factors which, in this case, would be the effect of the coast. Therefore, the dominant LEF in this situation would be ID4. It can be seen that, in general, the dominant factor is the proximity to coast (ID4,5,6) apart from where bridges are in areas of the highest galvanic corrosion (ID9).

Overall, the effects of the LEFs have been quantified and there is evidence to suggest that they are significantly different and therefore may even require different maintenance strategies.

Table 5.5: Table showing the dominant LEF in each category.

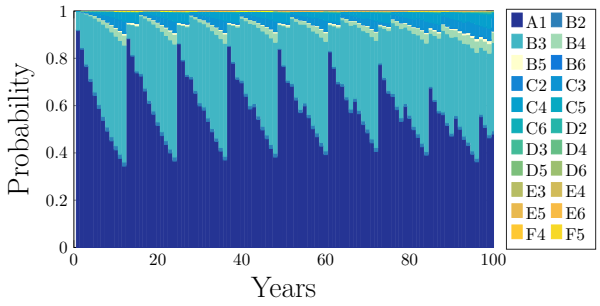
		Proximity To Coast		
Structure Type	Corrosion Rank	<5Km (ID4)	5-25Km (ID5)	>25Km (ID6)
Overline Bridges (ID2)	2,3 (ID7)	ID4	ID5	ID6
	4 (ID8)	ID4	ID5	ID6
	5 (ID9)	ID9	ID9	ID9
Underline Bridges (ID3)	2,3 (ID7)	ID4	ID5	ID6
	4 (ID8)	ID4	ID5	ID6
	5 (ID9)	ID9	ID9	ID9

Some exemplar model outputs can be seen in Figure 5.12 and Figure 5.13. The examples in Figure 5.12 show the elements all starting as new (A1) and then deteriorating at different rates. The sawtooth pattern is evident because of the inspection interval which then may lead to intervention. The inspection interval is 12 years for elements in good condition, however towards the end on the simulation the elements drop to a moderate condition and so the inspection interval drops to 6 years. Had they fallen to a poorer condition, the interval would have changed to 3 year intervals.



(a) Elements on bridges <5Km from the coast

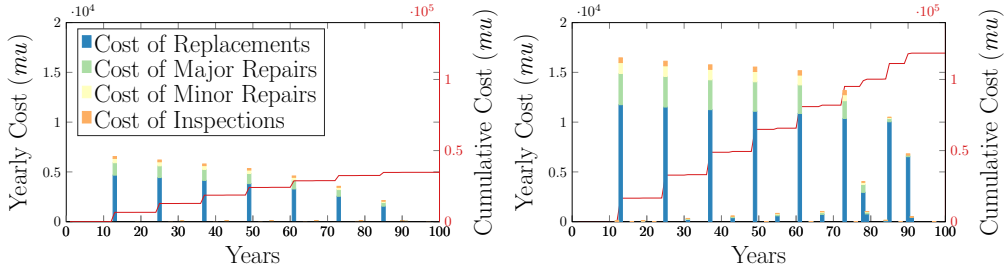
(b) Elements on bridges 5-25Km from the coast



(c) Elements on bridges >25Km from the coast

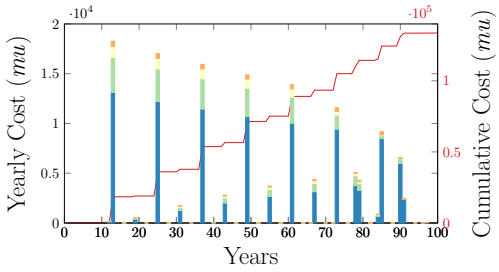
Figure 5.12: Graphs to compare the condition over time of various scenario model outputs.

Similarly, nominal and cumulative cost outputs (seen in Figure 5.13) show when maintenance is required, the type of maintenance and the typical cost, calculated from historical data. Again, it can be seen that the costs arrive in waves, originating from the inspection frequency - maintenance can only be scheduled when the condition of the elements is known. In some circumstances, as evident in Figure 5.13b, there are costs that are out of sync with the others; these originate due to rapid deterioration of the element. When the element deteriorates to a poorer condition state during the intervention scheduling delay; the maintenance teams attempt to carry out the intervention, however the defect has worsened beyond what they were expecting and so they will not have the available time/resources to carry out the repair and so it must be rescheduled. Elements in situations with more severe LEFs will be subjected to this more often as is



(a) Elements on bridges in galvanic response areas rank 2,3

(b) Elements on bridges in galvanic response areas rank 4



(c) Elements on bridges in galvanic response areas rank 5

Figure 5.13: Graphs to compare the cumulative cost of various scenario model outputs.

evident when comparing figures 5.13a, 5.13b and 5.13c. The result of an element being in a more severe LEF is that it will require more maintenance, increasing its costs, as well as being harder to manage due to the scheduling delay issue. For railway portfolio managers this situation can introduce further complexity when attempting to maximise maintenance team effectiveness.

The approach taken in this research was to develop a framework for a generic bridge model (see Chapter 4) and then determine if there was evidence to calibrate the model for different bridge groups based on the analysis performed using the critical path (see Section 5.2). If the evidence suggested that the groups of brides should be treated differently, then the model was calibrated with individual sets of deterioration parameters accordingly. From this simulations could be carried out to determine the WLCC impact of these LEFs. Another approach, which was considered, was to artificially divide the population of bridges into different groups,

perhaps based on existing literature or expert opinion, then to calibrate the deterioration parameters for those different groups and then run simulations to see if the behaviour of the groups were similar or not. It was determined that a generic bridge framework would be advantageous in its own right and so the first approach was taken in this research.

5.6 Local Environmental Factors (LEFs) Conclusion

There are many studies that focus on bridge deterioration modelling (Morcous et al., 2002a; Sobanjo, 1997; Arditi and Tokdemir, 1999) with a brief mention of the "other" factors that were not considered. Many authors suspect that these other factors may play key roles in the method of the deterioration, sculpting the deterioration profile in a different way. However, to conduct a study into these other factors requires a large amount of data, a suitable methodology and a modelling framework that is flexible enough to accommodate them.

In this research, a number of different factors were investigated, using a wide variety of data from historical weather data to corrosion data and even track performance data. A number of key factors that influence deterioration were identified, denoted as Local Environmental Factors (LEFs). Each LEF corresponds to a different environmental stressor that affects the deterioration of bridges subjected to that stressor, resulting in a different deterioration profile for each LEF. These deterioration profiles are used in the calibration of the stochastic transitions in the deterioration module of the PN model. With this capability it allows simulation of elements exposed to different LEFs to be simulated. Each of the LEF scenarios within the PN model were run in a comparative simulation which produced results from which the most important LEFs could be identified.

In this research it was identified that the structure type, coastal proximity and the galvanic response rank were the key LEFs. There were key findings for bridge managers including the effect of the coastal environment. It was found that, for example, bridges closer than 25km to the coast deteriorate at a rate 1/3rd higher than inland bridges. Understanding the impact of the coast and its extent inland is vital information for bridge portfolio managers.

Another development which is integral to the management of railway bridges is the impact of galvanic response which seemed to produce the most dramatic change in WLCC over the simulation period. Elements in areas of low galvanic response seem to deteriorate much more slowly accruing only a quarter of the baseline cost over their lifetimes. However, elements in areas of high galvanic response seem to suffer from accelerated corrosion and incur more then three times the cost of the baseline scenario. For infrastructure operators and managers, this result could have a large impact.

In conclusion, a novel approach to comparing two 2-D condition state systems was developed. From which a number of possible factors affecting bridge deterioration were investigated. From those, the key LEFs were identified and processed into individual scenarios, each with their own deterioration profiles. This allowed the railway bridge PN model to be enhanced with the LEFs which enables the ability to dynamically change the profile of the element deterioration based on the particular element characteristics. Finally, an investigation with a comparative simulation was carried out which identified which of the LEFs would be the most financially important to bridge portfolio managers.

The next chapter delves into the variability in the system regarding inspections and maintenance.

Chapter 6

Variability in Inspection and Maintenance Procedures

A number of studies have modelled bridge asset management from different hierarchical levels, using a plethora of modelling techniques under a variety of assumptions (Frangopol et al., 2004; Miyamoto et al., 2000; Morcous et al., 2002b). However, in the creation of models, sometimes the system can be interpreted in such a way that the resulting model is oversimplified. Perhaps assumptions made during the modelling mean that the advice given to the portfolio managers cannot be implemented. One major factor is neglecting that many of the processes that govern bridge management are decided upon by human intervention, which is prone to error. With this in mind, trying to incorporate misdiagnoses of defects and variability in intervention quality and cost can help improve the robustness of the model to the system.

6.1 Review of Variability in Inspection and Maintenance Procedures

To be able to incorporate system variability into a model, a great deal needs to be known about the system and the decisions made in each of the processes. Madanat (1993); Ben-Akiva et al. (1993) state that there are two fundamental sources of asset condition variability: the current condition of the asset and the projected condition of the asset. The authors identify that the current condition of the asset, determined during inspections, is prone to errors arising from: measurement errors, defect diagnosis errors and data input errors amongst others. Therefore, a misdiagnosis during an inspection can lead to major consequences with regards to incorrect maintenance being scheduled. They argue that policies are designed to recommend a suitable maintenance decision which means that a misdiagnosis can only lead to scheduling a maintenance action that is not as suitable. This increases the Whole Life-Cycle Costing (WLCC) of the asset which has detrimental effects for bridge portfolio managers. In their model, the authors assume that the condition reported by the inspection can contain errors and suggest that the reported condition should be probabilistically related to the actual condition of the asset. A parametric study is performed to ascertain the effect of variability on the final model outputs. The results seem intuitive as the larger the standard deviation, which represents a greater amount of variability, the higher the WLCC of the asset over its lifetime.

Phares et al. (2004) and Moore et al. (2001) investigated the variability in the results of inspections on highway bridges. They collaborated with 49 bridge inspectors who have been trained to the National Bridge Inspection Standards (NBIS), which is the standard in the US. The inspectors conducted 10 different field tests across a range of different types of bridges. The conditions reported by the inspectors were compared against

the Federal Highway Administration (FHWA) Non-destructive Evaluation Validation Center (NDEVC). The NDEVC condition was used as the true condition reading and each of the inspectors condition score compared. When taking the NDEVC condition as the true condition, the results showed that 78% of the condition scores reported by the inspectors were incorrect at a 95% probability. The study concluded that the vast majority of condition ratings (95%) will be within two condition scores of the true condition.

Neves and Frangopol (2010) conducted a study which includes the variability of inspections on bridges. The authors state that there are a number of factors affecting the quality of inspection data: the amount of experience the inspector has, available access to the element being inspected, the configuration of the bridge and the type of defect. With these factors in mind, the study relates the quality of inspection to the probability of misdiagnosis; a good inspection will only have 5% probability of misdiagnosis whereas a poor quality inspection has a 40% probability of being misdiagnosed.

Kuhn and Madanat (2005) conduct a study in which both implicit and explicit system variability are used. Implicit variability is in the form of the stochastic deterioration process, which has intrinsic variability. The author states that more recent bridge deterioration models recognise that the parameters used for deterioration can be uncertain. Explicit variability is defined by the authors, effecting each parameters used in the model. The authors carry out an optimisation comparison with one scenario including variability and one without. They argue that system variability built into the models is often calibrated with expert judgement which has intrinsic variability and therefore introduces a further layer of variability into the model. The results of the study show that with an increasing value of variability there is increasing overall costs.

A number of studies have been performed to try to grasp the effect of variability on bridge asset management modelling. Madanat (1993) identi-

fied that asset condition variability would have a major impact for bridge portfolio managers due to the effect of defect misdiagnoses. This had the possibility to cause organisational and financial problems with scheduling maintenance due to erroneous condition reports. Phares et al. (2004); Moore et al. (2001) tried to quantify the variability of inspections with a comprehensive field test. The results showed that in the vast majority of cases, inspectors were close to the mark, but still not correct. Using this information, Neves and Frangopol (2010) tried to formulate different tiers of inspections with good inspections having the least amount of variability.

It is clear that variability plays a large, but mostly neglected role in bridge asset management and therefore attempting to model the variability is worthwhile.

6.2 Sources of Inspection and Maintenance Variability

6.2.1 Inspection Variability

As mentioned earlier, Phares et al. (2004) studied the variability of identifying defects on bridge assets. The condition scale used in this work was 1-dimensional however, the one being used in this research is 2-dimensional. The deterioration data used for this research was extracted from the raw inspection data, received in the Severity Extent Rating (SevEx) format. The cleansing of the inspection data was carried out with the assumed definition that deterioration was the movement of element condition to the immediately neighbouring states of poorer condition. The justification of this assumption is that a monthly time step is used throughout this research and deterioration would not exceed this. This assumption was reinforced by expert opinion, more details can be found in Section 4.2.4.1.

Based on the observations made during data analysis, it seems that

most inspectors get the condition correct to ±1 condition state. The SevEx states are two dimensional in the sense that they span in both Severity and Extent. This means that for a particular reference state, there may be up to 8 surrounding states within the ±1 condition range, as seen in Figure 6.1. In this example, an element in condition state C3, which is a state only requiring Minor Repair according to the industry guidelines, could result in inspection results including condition states C4, D3 and D4. These condition states, under the industry guidelines, would require a Major Repair to be rehabilitated. Therefore, a misdiagnosis of the defect would directly result in the incorrect maintenance action being scheduled.

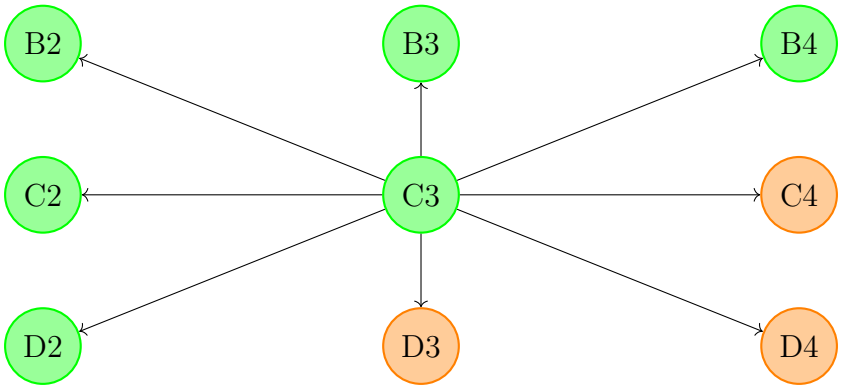


Figure 6.1: Diagram showing the variability in inspections.

The consequence of an erroneous identification is that it could lead to the wrong type of maintenance being scheduled. To calculate the probabilities of this occurring, each SevEx state was taken in turn and the surrounding states analysed to determine if the corresponding maintenance action would have been the same as the one corresponding to the original condition. This allowed the probability of the correct maintenance action being scheduled to be calculated for each SevEx state, presented in Table 6.1. Where condition states are on the border of two different corresponding interventions, the probability of a misdiagnosis leading to an erroneous maintenance action is higher. For conditions that are not near a border, if they are misdiagnosed, it is not as critical because the same intervention

is likely to be scheduled. It can be seen that on average, when inspections are within ±1 condition, maintenance actions are scheduled correctly 72% of the time (calculated as the average of the probabilities in Table 6.1).

Table 6.1: Table containing the probabilities of surrounding condition states which would lead to the same maintenance action being selected.

State	B2	B3	B4	B5	B6
Probability	1.00	0.80	0.40	0.80	1.00
State	C2	C3	C4	C5	C6
Probability	0.80	0.63	0.63	0.75	0.80
State	D2	D3	D4	D5	D6
Probability	0.40	0.63	0.75	0.63	0.40
State	E2	E3	E4	E5	E6
Probability	0.80	0.75	0.63	0.63	0.80
State	F2	F3	F4	F5	F6
Probability	0.60	0.50	0.63	0.88	1.00
State	G2	G3	G4	G5	G6
Probability	0.33	0.60	0.80	1.00	1.00

6.2.2 Imperfect Repairs

Typically bridge management models either do not consider maintenance explicitly or assume that maintenance is perfect (i.e. improves the condition to a perfect/predefined condition state) (Morcous and Lounis, 2006; Le and Andrews, 2013; van Noortwijk and Klatter, 2004). This assumption is often unrealistic, however historical maintenance data is required to dispense with the assumption. Therefore, data analysis was carried out with historical inspection records to determine the variability in the condition uplift after intervention.

The inspection data available for this research (see Section 4.2.1) contains details of element condition movement, including both deterioration and improvement. To be able to extract maintenance data from the inspections, the following must be disregarded: 1) situations where the element condition deteriorates 2) situations where the element remains in the same

condition 3) situations where the element improves by one condition condition state (due to the reasons discussed in Section 6.2.1). Additionally, improvements to elements whose state would require further repair were disregarded as they would have another maintenance action scheduled soon after and so are considered as a single maintenance action for this analysis. The occurrences of this situation were minimal. This leaves only the information where the element condition improved more than one condition state. The number of element maintenance records used for the analysis totalled 49,300. Due to the recording procedures, the type of maintenance action is unavailable and so the data was considered to be homogeneous.

The results of the analysis are presented in Table 6.2. It can be seen that condition state A1, the "as new" state only accounts for 43% of all condition uplifts. This result is in contrast with the perfect repair typically assumed in literature as less than half of the maintenance actions actually result in being in an A1 condition. Condition state B3 holds the next highest probability at 29% with the rest of the condition states holding smaller probabilities.

Table 6.2: Table containing the probabilities of being repaired to each condition state.

State	A1	B2	B3	B4	C2	C3	D2
Probability	0.4282	0.0546	0.2929	0.1008	0.0064	0.1159	0.0013

6.2.3 Variability in Costs

A key factor in WLCC is costing the works done to the asset over time. When looking at historical data, it is clear that some of the maintenance types have a much more varied cost than others. Using a fixed cost may not always be most suitable, as sometimes the costs can vary greatly, especially with more comprehensive maintenance actions. For example, a Minor Repair is only available to elements that have minimal amounts of deterio-

ration and so the cost of a Minor Repair can be predicted more accurately. On the other hand, replacement of an element is much more variable as it depends on the bridge configuration, the available access and if there are any design works associated with the replacement element, therefore, the cost of replacements is much more variable.

The CAF and MONITOR datasets contain information regarding works carried out and their associated costs. However, there were only approximately 250 records of costs of works carried out on concrete main girders, the exemplar elements in this research. Therefore, the statistics calculated from this dataset were combined with expert judgement to deduce the final values. It was decided that modelling and calibration of the costs should be carried out with the normal distribution. Although the data was calibrated with relatively few data points, the summary statistics were verified and tweaked by industry experts. Table 6.3 shows the parameters used to generate the costs in the Petri-Net (PN) model.

Table 6.3: Table containing the costs, in monetary units (*mu*), of the maintenance actions.

Maintenance Action	Mean Cost	Standard Deviation (SD)	Cost ±1 SD	Cost ±2 SDs
Minor Repair	140	30	110-170	80-200
Major Repair	400	100	300-500	200-600
Replacement	1,500	500	1000-2,000	500-2,500

6.2.4 Other Factors

6.2.4.1 Invariability of Inspection Interval

The inspection intervals are clearly defined in the industry policy guidelines. These policies are strictly enforced because the railway operator would be left exposed to significant fines from the Office of Rail Regulation (ORR). Therefore, the industry practices are to carry out the inspections precisely

when they are due. Thus, there is no implicit variability in the inspection intervals. Overall, the inspection intervals are not considered a source of variability in the model.

6.2.4.2 Structure Characteristics

Section 6.2.1 discussed the variability of inspections leading to the possibility of erroneous maintenance actions. Structures come in a variety of different forms and in some configurations may be easier or harder to inspect. A dialogue was initiated with senior bridge inspectors regarding the variability of inspections. It was made clear that all inspections are completed within touching distance (Network Rail, 2010e). Bridges that have more difficult access will require more specialised equipment (e.g. cherry pickers), but they must still be carried out within touching distance. Therefore the variability of the inspection data should be the same for all structure types.

6.2.5 Summary

Modelling of a system requires a certain balance between integrating key features, but avoiding overcomplexity. Bridge management is a difficult task that contains many processes. The features of the bridge management processes that are variable in nature should be incorporated into the model to reflect the variability that carries through to other processes. Due to the system complexity, there are many unknown sources of variability. The factors being investigated in this section have been chosen based on advice from industry experts, which either had available data with which to investigate or there was sufficient information from literature to perform an investigation.

The largest impact is with the subjectivity of the inspection process. There are many condition states and even though bridge inspectors must

obtain a certain level of training, interpretation and diagnosis of a defect introduces subjectivity. The way this affects the next process, deciding upon the appropriate maintenance action, means that if a misdiagnosis were to occur, then the wrong type of maintenance action may be scheduled. This has a knock on effect on the maintenance teams which may not have the appropriate resources/time to repair the element. These types of misdiagnoses can have organisational and financial impacts on railway infrastructure mangers.

Another feature added into the model is the maintenance effectiveness. By analysing historical maintenance data, the probabilities of being repaired to different condition states were found. The majority of interventions did not repair the element to the best condition (A1). By incorporating this attribute into the model, cycles of deterioration and intervention will follow a more realistic pattern.

Finally, analysis of historical financial information as well as expert judgement allowed variability of costs to be included in the PN model. This develops the realism of the model where inspection cost and intervention costs are variable.

In conclusion, a number of different attributes will be incorporated into the PN model which will bring the model closer to the real world system. This should provide greater confidence of the outputs due to the included features.

6.3 Incorporating Variability into the Railway Bridge Model

The variability in inspections, seen in Section 6.2.1, is embedded into the Maintenance Decision Module seen in Section 4.1.4. The way this is performed in the model is with probabilistic transitions which are embedded

with the probabilities specific for each condition state. For example, from condition state B3, the probability of selecting the correct maintenance action, which is a Minor Repair, is 0.8. The probability of selecting a Major Repair, which would be an incorrect maintenance action, is 0.2. Each of these probabilities is embedded into their corresponding transition in the PN model so that variability in inspections can be simulated. The full table of transition probabilities can be seen in Section C.2.

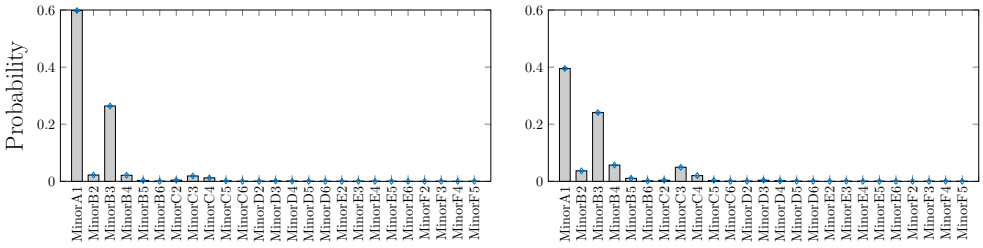
The imperfect repairs and variability in costs, seen in Sections 6.2.2 and 6.2.3, are embedded into the Intervention Module, seen in Section 4.1.5. The variability in costs are performed with another probabilistic transition where each of the resulting condition outcomes are calibrated with their corresponding probability.

6.3.1 Comparative Model Outputs

When running simulations with the railway bridge PN model, it is possible to enable or disable probabilistic transition functions. If enabled, the simulator will attribute the given probabilities to the chosen probabilistic transition. A like-for-like approach was used to obtain model results as those shown in Section 4.3 in order to compare the results with and without variability. A single concrete girder element with two sub-minor elements is used as the simulation example. The girder begins in the A1 condition for both simulations. The scenario with variability includes: maintenance decision variability where a defect misdiagnosis can occur, imperfect repairs rather than assuming repair improves the condition to A1 and variability in costs.

The first model output to be compared is the probability of the element residing in each of the condition states over the 100 year simulation. Figure 6.2 shows the outputs of the model with and without variability respectively. It can be seen in Figure 6.2a that, over the 100 year simulation,

the girder element spends 60% of its time in condition state A1. The reason for this is that when the element deteriorates, the Network Rail (NR) maintenance strategies are quick to detect the defect and repair it. The repair improves the condition back to an A1 condition in this scenario as maintenance actions are assumed to be perfect. Condition state B3 seems to be the only other state with a significant proportion of time; this is because the deterioration of elements from A1 often goes to B3 which is the first condition state which maintenance can be applied (minor repair). This scenario can be compared to Figure 6.2b, which includes variability in the model. The probability of the girder element being in condition state A1 over the 100 year simulation period is lower at only 40%. There is also more of a spread between the conditions states with B2, B4 and C3 playing a more major role in the deterioration profile of the element. It seems that condition state B3 is playing an equally significant role as in the scenario without variability. The results of this suggests that not only does imperfect repair spread the condition state probability, because of that it also changes the route the element deteriorates and therefore offers much more variability in the way the defect evolves over time.



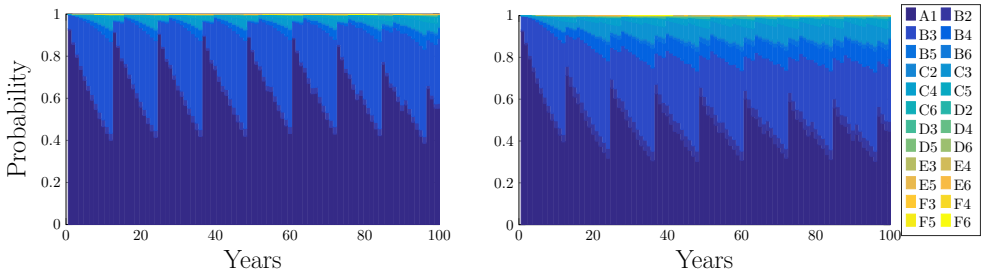
(a) Scenario without variability.

(b) Scenario with variability.

Figure 6.2: Probability of each condition state being occupied (99% CI).

The effect of imperfect repairs can be seen on the deterioration of the element. When comparing the graphs in Figure 6.3 it can be seen that both simulations start with the girder element in condition state A1, but, in a few cases some of the elements will have degraded by the end of the first year.

NR policy states that elements that are in a good condition should only be inspected every 12 years. Therefore the downward trend of the graphs show the deterioration of the structure until the scheduled inspection at year 12. At this point the inspection occurs and there is an associated condition improvement. The condition improvement in Figure 6.3a, the scenario without variability, jumps to an A1 condition state, representing perfect repairs. The condition improvement in Figure 6.3b, the scenario with variability, is much more variable as it represents imperfect repairs. For this reason the sawtooth pattern on Figure 6.3b is not as sharp as those seen in Figure 6.3a. It can also be noticed that on some of the downward sawtooths, there are small undulations. These occur when the second round of maintenance occurs due to a reschedule. These can occur in Figure 6.3a, the scenario without variability, because the element can deteriorate whilst the maintenance is being scheduled to a condition which they cannot repair with the resources available. However, these undulations occur more often in Figure 6.3b, the scenario with variability. Additionally, this is compounded by the possibility of a defect misdiagnosis which can lead to the wrong maintenance action being scheduled. These model outputs show the complexity of processes and how variability in one aspect of the model can impact another.

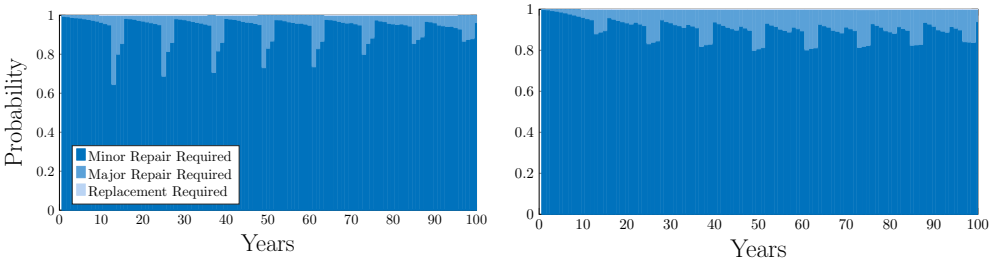


(a) Scenario without variability. (b) Scenario with variability.

Figure 6.3: Probability of being in different condition states over time.

Figure 6.4 shows which interventions would be necessary at each point in time over the simulation period. It can be seen that at the start of

the simulation, when the element is in good condition, both Figures 6.4a and 6.4b have a high probability of only requiring a Minor Repair. These model outputs show what intervention would most likely be required if an intervention were scheduled at that time. When comparing the two figures, the saw-tooth pattern in Figure 6.4a is more pronounced then in Figure 6.4b. This is because Figure 6.4a does not include variability in the simulation and therefore follows a complimentary pattern to that seen in Figure 6.3a. In Figure 6.4b the probabilities are much more steady and this is because of the effect of imperfect repairs. With imperfect repairs there is less of a condition change after rehabilitation which leads to a more steady set of probabilities across the simulation period.



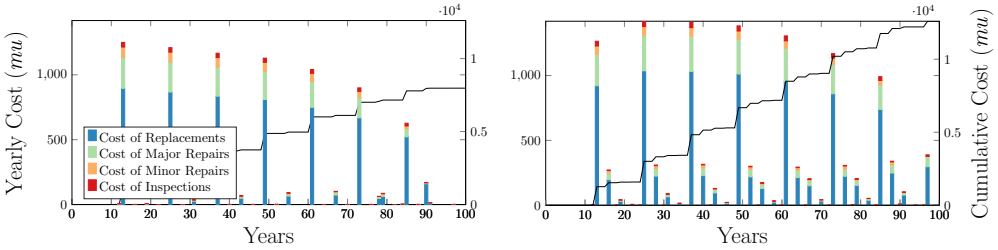
(a) Scenario without variability.

(b) Scenario with variability.

Figure 6.4: Probability of which intervention would be required over time.

The effect of maintenance decision variability and variability of costs can be seen in Figure 6.5. The stacked bars represent the cost each year of Inspections, Minor Repairs, Major Repairs and Replacements. The line graph represents the cumulative cost over the 100 year simulation period. Figure 6.5a shows the model outputs without variability. It can be seen that the intervention costs are regular, coinciding with the inspection frequency. This makes the expected cumulative cost very regular and predictable in nature. On occasion, where the element has deteriorated whilst maintenance was being scheduled, the works could not be completed. In this situation the maintenance teams would have to schedule and return to perform the correct maintenance action, hence the smaller bars occurring between the

major bars on the graph. When looking at Figure 6.5b, it is evident that there are many more situations where the maintenance teams are required to go back. This is due both to element deterioration and the fact that defect misdiagnoses are included. This would have a dramatic effect on the amount of work for the maintenance teams. This causes the cumulative cost to be more erratic and unpredictable which makes it harder for railway operators to manage. Additionally, because of the imperfect repairs considered in the scenario, deterioration will most likely be at a later stage which means that the maintenance action required will be more severe and therefore the costs will be higher. This, compounded with the variability in costs, has meant that the cumulative cost in Figure 6.5b is almost double that of Figure 6.5a.

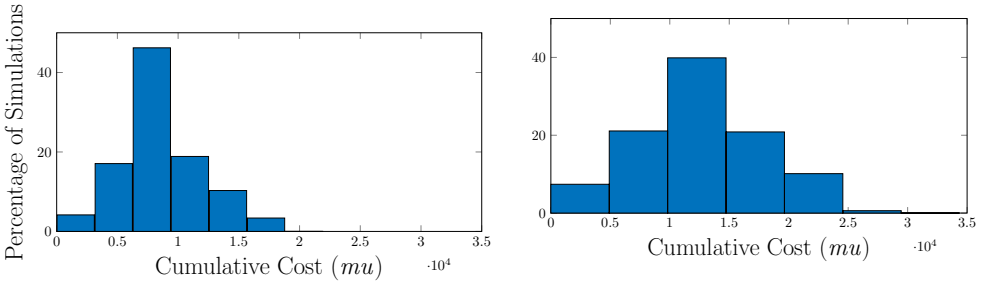


(a) Scenario without variability. (b) Scenario with variability.

Figure 6.5: Nominal and cumulative cost of repairs and inspections per year.

Figure 6.6 compares the distribution of cumulative costs across simulations. When comparing Figures 6.6a and 6.6b, it can be seen that the cost in Figure 6.6a, the scenario without variability, the overall costs are lower as well as having less spread. Figure 6.6b has both higher costs, and a wider spread of costs, representing a more real-world result. It can be seen that the majority of the simulation outputs result in cumulative costs in the range of 6,000-10,000mu in Figure 6.6a whereas the majority of the simulation outputs result in cumulative costs in the range of 10,000-15,000mu in Figure 6.6b. This is an expected result as introducing variability in the maintenance aspects will have an effect on the costs, however the results

are more true-to-life and an essential feature for decision making.



(a) Scenario without variability.

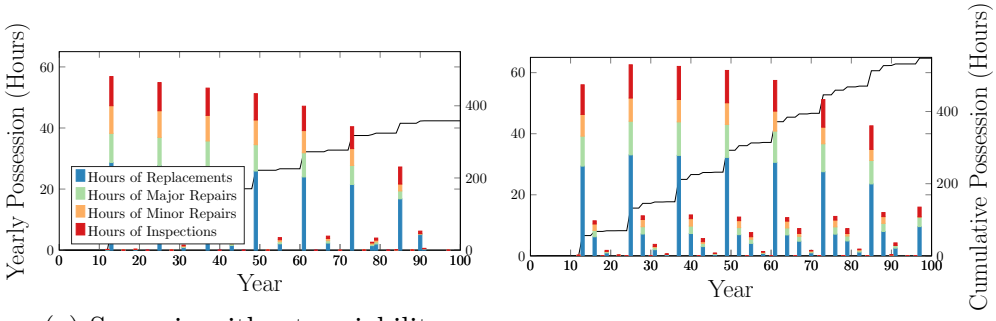
(b) Scenario with variability.

Figure 6.6: Distribution of cumulative costs over the 100 year simulation period.

Figure 6.7 shows the amount of nominal and cumulative possession hours for inspections and maintenance per year. It can be seen in Figure 6.7a that the bars are quite regular, this will be because, in this scenario, there are no defect misdiagnoses and so the only time when maintenance would have to be rescheduled is if the element deteriorates to a worse state, requiring a different type of maintenance, and the maintenance teams must reschedule. Overall the cumulative amount of possession hours over the 100 year simulation is estimated to be 360 hours. Figure 6.7b shows the scenario which includes variability. It can be seen that the bars of the bar chart are much less regular. This is because of the added complication of misdiagnoses. When an inspection occurs and an element is misdiagnosed, the subsequent intervention may have to be rescheduled if an unsuitable type of rehabilitation has been requested. It can be seen that this causes quite a significant increase in the cumulative possession over the simulation; increasing to a total of 550 hours. By considering defect misdiagnoses in the model, the amount of possession required has increased over 1.5 times over the simulation period.

Overall it seems that including variability in the PN model has a dramatic effect with each of the processes impacting on the next which is exacerbated for bridge portfolio managers who have to manage a large

population of these assets.



(a) Scenario without variability.

(b) Scenario with variability.

Figure 6.7: Nominal and cumulative possession hours of inspections and maintenance per year.

6.4 Summary of Variability in Inspection and Maintenance Procedures

This chapter investigated the causes of variability in some of the processes of bridge asset management and then incorporated them into the railway bridge model. The railway bridge PN model was modified to address the following occurrences of variability within different phases of the bridge asset management process: 1) variability in defect diagnosis causing the wrong type of maintenance to be scheduled, 2) variability in the intervention process so that there is some variability in the condition improvement and lastly 3) in the variability of costs as intuitively, not all repairs will cost the same amount. Historical data and expert judgement was used to calibrate the variability in the processes.

Two sets of simulations were preformed. First, the basic model, neglecting the variability. Then, simulations of the model taking into account the variability of the processes aforementioned were performed. What was most evident was that variability built into one part of the PN model was impacting the subsequent parts. A misdiagnosis of the defect can lead to the

wrong maintenance action being scheduled, this causes time inefficiencies for the maintenance team, wasting capital and leaves the bridge in a deteriorated state until the maintenance team have time to come back with the appropriate resources. Additionally, when considering that the intervention process is variable too, this means that the deterioration of the elements will be more advanced as well as the starting condition is not from a perfect condition. This means that the inspection process is even more critical as the element may be on the threshold of a more major intervention.

Overall, it can be seen that bridge asset management is a complex process which involves many tasks, each with its own potential for variability. This variability can have real impacts on the management of a portfolio of structures as it could result in an inefficient and ineffective use of inspection and maintenance teams which further reduces budget performance. The results of this chapter show that even moderate amounts of variability quickly build up in the system to make the whole process much more complex and much more capital intensive to manage (both in terms of financial and operational burden). Adding in these features adds to the realism of the model and usefulness of the outputs, but also increases the computational burden. Therefore, next chapter focuses on improvements which can be made to the computation of the model to speed up execution.

Chapter 7

Accelerating Petri-Net (PN) Simulations

Petri-Nets (PNs) have been gaining in popularity in the field of Asset Management (Andrews, 2013). One of the limitations of PNs in conjunction with probabilistic transitions is the requirement for Monte Carlo (MC) simulations resulting in high computational cost. High computational cost often means extended execution times, which would limit the adoption of the approach as a decision support tool. Additionally, decision optimisation could be impractical if the computational cost is too high. Therefore, it may be worth investigating if acceleration is possible to perform on the model to reduce the execution time. This chapter details an investigation into whether it is possible to accelerate simulations of complex PN models. Studies have been undertaken into accelerating simulations of PNs with General-Purpose Graphics Processing Units (GPGPUs), however these have mostly been in the fields of Biology and Physics.

The use of MC methods is very popular in science, engineering and economics research. Over time MC-based models have become progressively more sophisticated which often means longer computation times, limiting their applicability. The use of Graphics Processing Units (GPUs) in

academia as GPGPUs is gaining in popularity as it has the potential to dramatically decrease computation time allowing for much faster throughput. At the same time, the technological development of GPUs and their progression into general computing has meant that the cost per computing unit has dropped significantly.

This chapter investigates the suitability of GPGPUs to accelerate simulations of the railway bridge PN model. A simple PN example is used as a proof of concept and then the same approach is applied to the railway bridge PN model.

7.1 Review of Accelerated Simulations using GPGPUs

A number of studies have been undertaken in the field of Physics to accelerate MC-based models with GPGPUs. Although not directly related to PNs, the application of the GPGPU to the modelling approach is relevant.

Tomov et al. (2005) performed a study to investigate the suitability of GPGPUs with 2D and 3D Ising models. An Ising model represents the spin of magnetism in a lattice structure. Each of the magnets can be in one of two states. The model becomes more complex when considered in a 3D space. The authors state that the common way of incorporating MC methods into the Ising model is to choose a random path through the magnets, at each magnet generating a random number which decides whether the spin should be reversed or not. At this time the Compute Unified Device Architecture (CUDA) framework (the standard framework for GPGPU development currently) was yet to be established and so an older framework known as Cg was used. The GPU used was an NVIDIA NV30, a high-end GPU from 2003. The author concludes that the GPGPU implementation of the Ising model is three times faster than the Central Processing

Unit (CPU) implementation on average. This holds true for both the 2D and 3D examples tested. The authors mention that the GPGPU performance may have been limited due to branching as the contemporary GPU used for this study did not support this feature.

Preis et al. (2009) also performed a study using GPGPUs on Ising models, testing both 2D and 3D models. They used an NVIDIA GeForce GTX 280, a high-end GPU from 2008. The CUDA framework had been released by this time. They use a checker-board pattern approach to make the computation more efficient. They achieve a 60 times speed-up factor in the 2D Ising model test and a 35 times speed-up factor in the 3D scenario.

Yang et al. (2007) used the power of GPGPUs to accelerate molecular dynamics. The study involved simulations to calculate thermal properties. The process of simulating molecules involves a 3D grid of interacting nodes. Simulations are carried out where the amount of energy passed from atom to atom is recorded. The stochastic nature of the modelling is due to the movement of molecules based on a decision which uses random numbers. They used an NVIDIA GeForce 7800 GTX, a high-end card from 2005. They used the Cg programming framework with 600,000 iterations per simulation. The number of atoms in the simulation was tested against the execution time. The results show that the execution time almost follows an exponential curve with the number of atoms in the simulation. In every test, the GPGPU execution is quicker than that of the CPU. The authors conclude that their average speed-up factor is between 10 and 11 times using the GPGPU.

van Meel et al. (2008) also use GPGPUs with molecular dynamics. They implement the N-squared molecular dynamics algorithm for their simulations. In contrast to Yang et al. (2007), the CUDA framework had been released by this point. They perform an interesting comparison between the simulations performed on (1) a CPU, (2) GPGPU with Cg and (3) GPGPU with CUDA. As well as the update in programming framework, they use

a newer GPU from Yang et al. (2007): an NVIDIA GeForce 8800 GTX. Their results show that the GPGPU with Cg performs around 40 times faster than the CPU implementation. Using the newer CUDA framework, they manage an 80 times speed-up factor over the CPU execution.

Geist et al. (2005) was one of the first studies to try to accelerate PN simulation with GPGPUs. They use an NVIDIA GeForce 6800 Ultra, a high-end GPU from 2004. The authors create a PN simulator using Cg called "Cgpetri". They compare this to serial PN simulators "xpetri" (Geist et al., 1994) and "SPNP" (Hirel et al., 2000). The example of the dining philosophers was used in the study, created by E. W. Dijkstra, but formalised by Hoare (1978). This is a common example of a PN with conflict conditions. These arise because each philosopher requires two forks to eat with, however there are too few forks to satisfy each diner. Therefore, the resource must be shared which means that the diners alternate between two condition states. They test the example ranging from 25 diners to 400 diners, recording the execution time. When there are few diners, execution on the CPU is faster as the data does not need to be packaged, passed to the GPGPU and then transferred back after computation. However, the critical point in this example is at 50 philosophers; beyond which the GPGPU based simulator seems to be faster. The serial simulators follow an almost exponential execution time with the number of diners, however when run with Cgpetri the execution time only seems to double from the minimum number of diners to the maximum.

Geist et al. (2005) also apply this approach to a Lattice-Boltzmann example. This is commonly used for fluid dynamics where a series of partial differential equations are to be solved. The more points that are created in the simulation, the more detailed the resulting outputs. There has been studies performed to parallelize Lattice-Boltzmann models and a common approach is to divide the problem into "subcubes" for concurrent computation. The authors propose a PN to schedule the computation of these

subcubes to increase efficiency. Again they compare Cgpetri to xpetri and SPNP. They increase the number of places in the flow net, recording the execution time. Again, it can be seen that when the number of places in the flow net is small, the overhead of using the GPGPU means that the execution is slower. However, the advantage of the GPGPU quickly shows its strength as the execution time is almost the same across the whole range of places tested whilst the serial simulators experience significant slow down. The authors close with a comment that Moore's Law, a characteristic applied to CPU development, means that their performance seems to double every 18 months (Schaller, 1997). However, the rate of development of GPUs is closer to doubling every 6 months. Therefore, not only was the GPGPU already accelerating the simulations but the difference was set to increase even more.

Chalkidis et al. (2011) also attempt to accelerate PNs with GPGPUs. They use a real world example from the field of biology, specifically microbiology, and medicine. They use the CUDA programming framework with an NVIDIA GeForce 8800, a mid-range GPU from 2006. They explain that they use Hybrid Functional PNs and detail its decomposition for GPGPU programming. They mention that the possible acceleration could be significant if they could parallelize their PN. They do so by splitting their PN into three processes hierarchically. Processes one and two are able to be simulated concurrently as they do not interact directly. Then process three can use the results of processes one and two to finish the simulation. Theoretically, by using this approach the PN simulation could experience a 1.5 times speed-up factor in serial operation. However, when considering the massively parallel characteristic of GPUs, the speed-up could be significantly higher. They conclude by saying that their average PN acceleration when using the GPGPU was 18 times faster than the serial execution.

In summary, a number of studies have been undertaken accelerating simulations in the fields of Physics and Mathematics. Table 7.1 shows the

results of the average speed-up factor in each of these studies. It can be seen that earlier implementations using Cg did not provide as much speed-up as later versions using CUDA. This will be because: (1) the CUDA framework provided updated algorithms, processes and techniques which would help efficiency and (2) although the studies were carried out with contemporary CPUs and GPUs, the advancement of GPU compute capability outstrips the development of CPUs and so the difference in compute performance grows with time.

Table 7.1: Results of the execution time of a simple PN when computing on various devices.

Study	Approach	Framework	Speed-up Factor
Tomov et al. (2005)	2D, 3D Ising Model	Cg	3
Yang et al. (2007)	Molecular Dynamics	Cg	10-11
Chalkidis et al. (2011)	Hybrid Functional Petri-Nets	CUDA	18
Preis et al. (2009)	3D Ising Model	CUDA	35
van Meel et al. (2008)	Molecular Dynamics	Cg	40
Preis et al. (2009)	2D Ising Model	CUDA	60
van Meel et al. (2008)	Molecular Dynamics	CUDA	80

7.2 Example Algorithm for Petri-Net (PN) Simulation

An example algorithm for PN simulation can be seen in Figure 7.1, represented by a flow diagram. The initial set-up of the PN is represented as an input node as often there will be some processing of data to construct the PN. Then the number of samples required will be represented by a loop. Within each of the samples there will be a further loop. This process starts with the checking of the transitions to see which are enabled (stage 4 in Figure 7.1). This can be quite a computationally expensive process as every

transition needs to be checked to see if all its input places are marked (contain at least one token) and there are no active inhibitors on the transition (Jensen and Kristensen, 2009). The transitions which are enabled can then generate a transition firing time; stochastic transitions would call random numbers at this stage. Conflicts (i.e. two transitions are due to fire at the same time using the same input tokens) must be avoided (stage 6 in Figure 7.1). Two transitions with the same transition time that do not interfere with each other can fire simultaneously. The enabled transition(s) with the shortest transition time would be selected for firing. The simulation time is then increased to the point of the next transition firing. Upon firing, the input tokens are removed from the places. New tokens are generated in the output places (Andrews, 2013). Stage 9 in the figure represents a post-firing check which is to remove any transitions which were marked as enabled but are no longer enabled as the token has moved from the input place. The simulation time is checked to see whether the required simulated period has finished (e.g. 50 years). If not, the process restarts from stage 4. When the simulation time has elapsed, the sample is complete. Stage 11 checks whether the required number of samples has been run. Stage 12 aggregates the results, this is represented as an output node as often the results will be analysed afterwards. Finally, the algorithm terminates.

7.3 Parallelizing Petri-Nets (PNs)

There are a number of different ways to parallelize PNs. Chalkidis et al. (2011) demonstrated a PN which could be split up for the purposes of parallelization. The overall PN was split up into three sections. The two independent sections of the PN were simulated in parallel to reduce compute times. Then the third was able to aggregate the outcome of the two independent sections to simulate the overall model outcome. The advantage of this method is that it promotes hierarchical PNs where a number

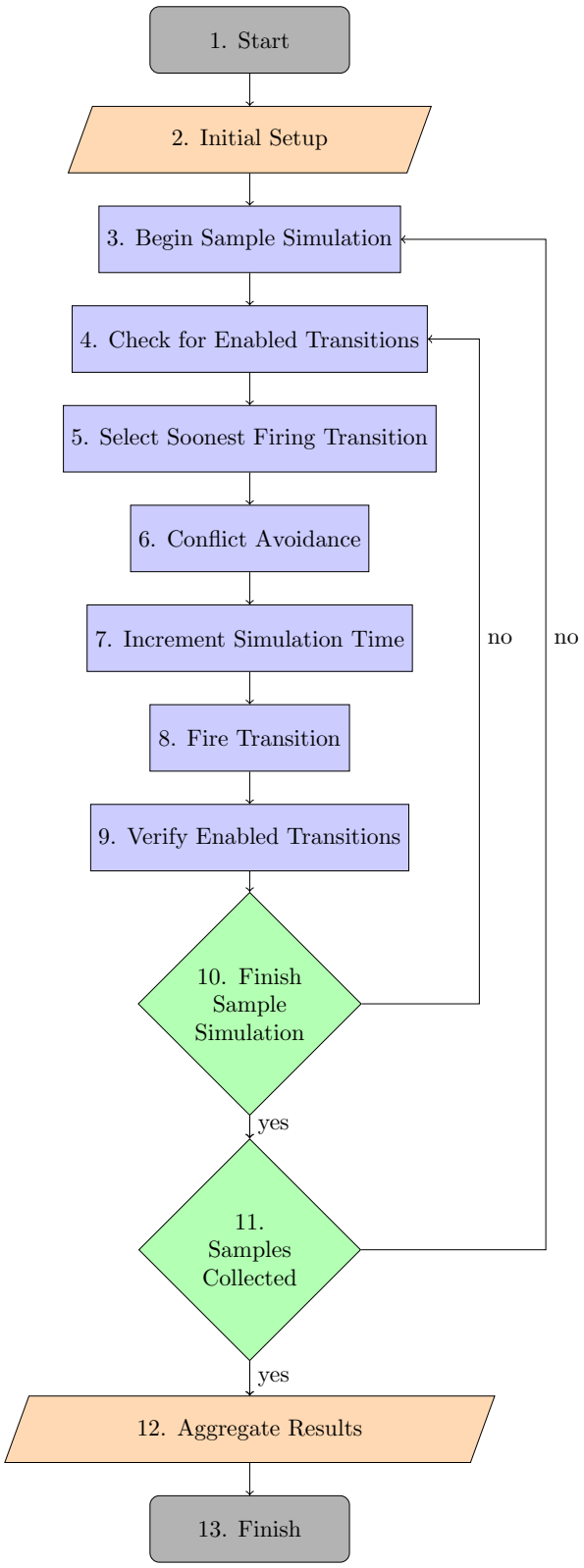


Figure 7.1: Flowchart of a stochastic Petri-Net (PN).

of sub-nets can be simulated in parallel. The nets further up the hierarchy are then able to continue with the simulation aggregating the outcome of their subordinate sub-nets.

Some systems are not able to be modelled with independent sub-nets. In these instances, an alternative parallelisation approach must be used. Rather than trying to parallelize the PN itself, the MC method can be parallelized. In this method, the number of samples required is selected. Each sample is executed on an individual thread which takes the initial set-up data, carries out the simulation and then passes back the necessary variables. An example schematic can be seen in Figure 7.2. The section labelled "Sample Simulations" could include Stages 4 to 10 of the PN algorithm in Figure 7.1.

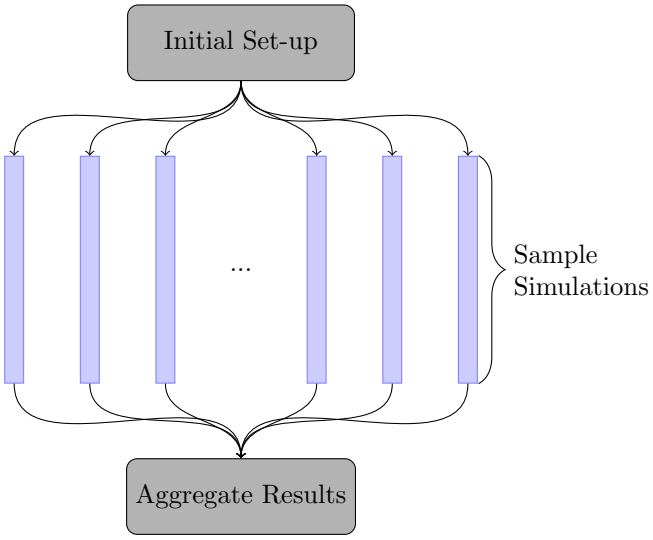


Figure 7.2: A schematic demonstrating how a group of MC samples can be executed in parallel.

7.4 Processing Units

7.4.1 Central Processing Units (CPUs)

All computers contain a CPU which could be considered the centre of compute functionality. Traditionally, the CPU only contained one core on which to perform calculations. More recently, multi-core CPUs have become available which are able to perform multiple calculations simultaneously. Due to industry technologies, however, a dual-core system may be able to perform more than two calculations in an instance. For this reason compute capabilities of a processing unit are compared in terms of the number of "threads" which the processor is able to utilise at any given moment. For example, a modern CPU may have four cores which could support up to eight threads.

A typical schematic of a CPU is shown in Figure 7.3. The CPU contains some fast temporary storage as well as some control circuitry. These all serve to provide the cores with the data they require, maximising throughput. The example CPU in the figure contains four cores which is typical of a modern CPU.

7.4.2 Graphics Processing Units (GPUs)

A GPU is not a component which is mandatory to the make-up of a computer, unlike a CPU. Its original purpose was for rendering graphics and has had considerable success in creation of animated films where vast arrays of GPUs help to speed up production (Apodaca et al., 2000). Their classic role was to take a small piece of data, for example representing the colour of a pixel in the frame of a film, and apply a function to it. The more pixels that could be processed at once, the faster the production of the overall frame would be. Hence, the evolution of the GPU as a massively parallel processing unit.

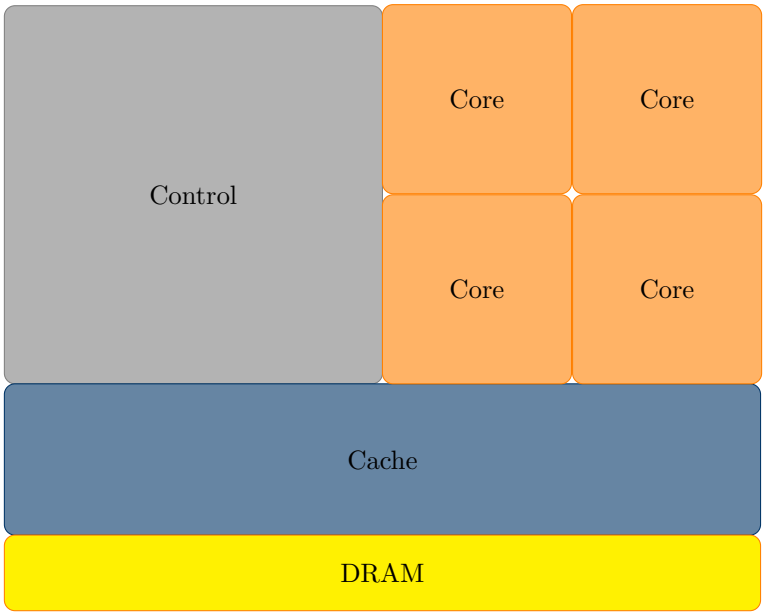


Figure 7.3: A schematic of a typical CPU, recreated from NVIDIA Corporation (2015).

In comparison to CPUs, a GPU may have many more cores, but each individual core is slower. A schematic of a GPU can be seen in Figure 7.4. It can be seen that there are many more cores than the CPU seen in Figure 7.3. Additionally, rather than the whole processing unit sharing the cache and control units, there are multiple cache and control units. This is because GPUs often have so many cores that they are organised into a hierarchy (see Section 7.4.3.2).

7.4.3 Comparison of CPUs and GPUs

A typical CPU contains fewer faster cores whereas a typical GPU contains many slower cores. To be able to compare computational output of the processing units, the number of Floating-Point Operations Per Second (FLOPS) is computed using Equation 7.1.

$$FLOPS = sockets \cdot \frac{cores}{socket} \cdot clock \cdot \frac{FLOP}{cycle} \tag{7.1}$$

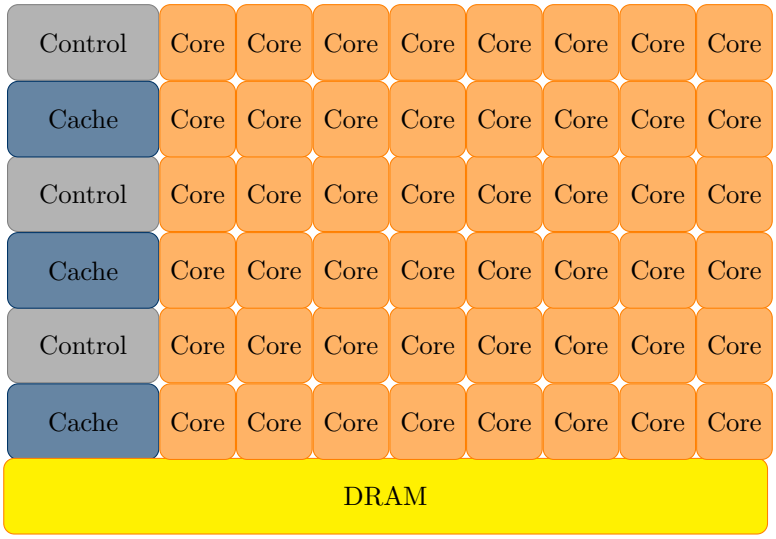


Figure 7.4: A schematic of a typical GPU, recreated from NVIDIA Corporation (2015).

where *sockets* refers to the number of devices in use, *cores* refers to the number of compute cores in each device, the *clock* refers to the frequency of the cores and the $FLOP/cycle$ is based on the architecture of the core with modern devices being able to compute 4 floating point operations per cycle (Hunt, 1995).

Figure 7.5 shows the aggregated results of the best CPUs and GPUs, in terms of FLOPS, back to the year 2000 (NVIDIA Corporation, 2015). The scale on the y-axis is in TFLOPS (10^{12} FLOPS). It can be seen that the computational throughput of GPUs is far superior to CPUs. It is for this reason that accelerating MC methods on modern GPUs could be advantageous.

7.4.3.1 Compute Unified Device Architecture (CUDA)

The CUDA programming framework enables GPUs to be used for general programming tasks. GPUs which are not being used in their traditional role are referred to as GPGPUs. For clarity in this research, the physical hardware is referred to as a GPU, however when using it in a non-traditional

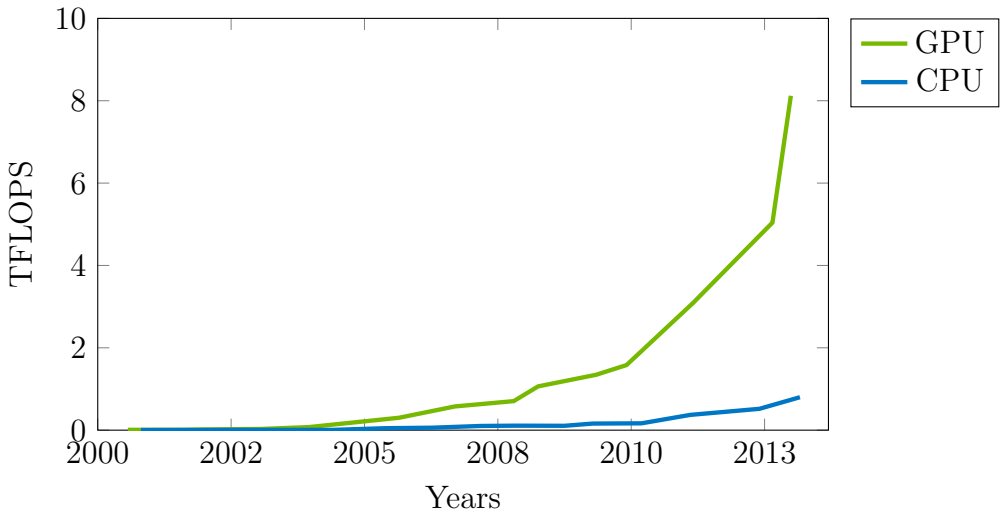


Figure 7.5: Graph comparing the computational throughput of the best CPUs and GPUs back to the millennium (NVIDIA Corporation, 2015).

role, as in this research, it is known as a GPGPU.

Other frameworks for programming on GPGPUs are available, however the CUDA framework seems to be popular in academia (Kirk and Hwu, 2010). The framework uses a Single Instruction, Multiple Thread (SIMT) programming model. This is geared towards performing the same operation on many different pieces of data. For example, an array could be worked on where each thread takes an element of the array and doubles it before re-inserting it into the array. In this example, every element is performing the same instruction but to a different piece of data. Given the number of elements in the array is fewer than the threads available, this effectively means that the time taken to carry out the operation on every element in the array is the same as to perform one operation in serial mode.

Programming with CUDA has become more user-friendly and accessible to those who code in C or C++ . The latest iterations of CUDA can hook directly into the users Integrated Development Environment (IDE) and includes a CUDA debugger as well as code profiler. Writing functions to be performed on the GPGPU are known as kernels. The kernels accept a limited form of the C language, however more features are being intro-

duced with every iteration of the CUDA programming framework (NVIDIA Corporation, 2015).

7.4.3.2 Grids, Blocks and Threads

Modern GPUs can have thousands of compute cores and are organised into groups for easier management. The Tesla K40 used in this research has a total of 2,880 cores organised into 15 groups, known as Next Generation Streaming Multiprocessor Units (SMXs), each with 192 cores. As mentioned in Section 7.4.1, the number of cores contained within a processing unit do not dictate the maximum number of calculations that can be completed in an instance. This is because of industry developments which means that cores are able to perform more than one calculation in an instance depending on the type of operation (Preis et al., 2009). For this reason the number of "threads" are used rather than cores.

In the CUDA programming model, threads are the individual compute entities that carry out the calculations. Groups of threads are known as blocks which have a maximum of 1,024 threads. Threads are launched in multiples of 32 known as a warp e.g. a block of 512 threads is arranged as 16 warps. In more recent iterations of the CUDA framework, a grid of blocks can be sent to the GPGPU for calculation. Depending on the compute capability of the GPGPU, 3 dimensional grids of blocks can be launched. The way these compute units are grouped is illustrated in Figure 7.6.

Each grid dimension can accommodate up to 65,536 blocks. For example, the maximum number of threads that can be launched on the Tesla K40 can be seen in Equation 7.2. This device is capable of 3 dimensional grids where each dimension can have a maximum of 65,536 blocks. Each block can have a maximum of 1,024 threads. Depending on the complexity of the operations being called, the CUDA cores will map one or more of these threads to themselves (Kirk and Hwu, 2010).

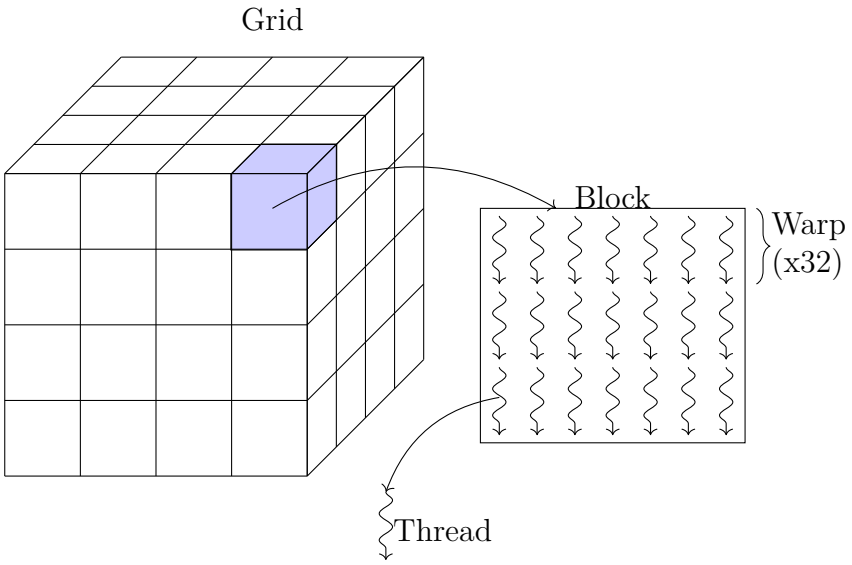


Figure 7.6: Diagram showing the hierarchy of blocks, warps and threads in the CUDA framework.

$$Maximum\ Threads = 65536^3 \cdot 1024 = 2.88 \cdot 10^{17} \tag{7.2}$$

7.4.3.3 Coding for GPGPUs

The architecture of a modern computer is such that the CPU and Random Access Memory (RAM) are in constant communication, known as the "host" in the CUDA programming model. When computing on the GPGPU, known as the "device" in the CUDA programming model, the host must send the kernel instructions as well as the data required for computation. The process of this is usually: (1) create/load the data on the host (2) allocate space for the data on the device (3) copy the data over to the device (4) launch the kernel on the device (5) copy the data back from the device to the host and finally (6) free the device memory. The communication between the host and device is through the Peripheral Component Interconnect Express (PCIe) lanes of the computer. Although the bandwidth of these lanes has improved (Ajanovic, 2008), transferring data between the host and device is still time in which no computation is being carried out.

Therefore, when coding for GPGPUs it is imperative that the data transfer be as lightweight as possible (Sanders and Kandrot, 2010).

On the subject of GPGPU memory, there are various types of memory each with its own purpose. The global memory space is large, but is slow to retrieve data from compared to the other memory types. The cache memory and registers are the fastest type of memory, however they are restricted in size. By keeping the amount of data as lean as possible, it will enable more efficient use of the cache and registers. Data in the cache/register is able to be retrieved much faster compared to the global memory which can increase computational throughput.

As explained in Section 7.4.3.1, GPGPUs use the SIMT parallel model which means that each thread gets the same instructions. Additionally, as mentioned in Section 7.4.3.2, threads are launched in groups of 32 known as warps. Due to the way the SIMT parallel model works, every thread in a warp carries out the same instruction at once. For this reason branching is a major performance limitation. Branching occurs when, for instance, an IF statement is provided in the code where some members of the warp satisfy the IF statement and others do not. In this instance the warp is split into two branches where each branch executes their sections in serial. This can be a serious performance limitation and so branching should be avoided if possible.

7.4.4 Generating Random Numbers

The PN railway bridge model uses a number of stochastic transitions which require MC simulation. Therefore, an efficient method for generating random numbers is essential to avoid computational slowdown. This is even more apparent after parallelisation because of the relative time of computation. As is usually the case with computation of random numbers on computers, a Pseudo Random Number Generation (PRNG) is used. Gen-

eral methods of using GPGPUs with PRNGs are: (1) if the quantity of random numbers is pre-determinable, a kernel can be written where each thread generates one or more random numbers storing them in an array. A common technique for this method is to use the individual thread ID as the seed value for the PRNG. (2) For situations when the quantity of random numbers is not pre-determinable, the PRNG can be built directly into the simulation algorithm. This way the random numbers can be generated on command.

A third approach was outlined for use in this research but was not required. This approach was for situations when the number of simulations required was not maximising the capability of the GPGPU. This approach used concurrent kernels working in collaboration. Kernel A would control the threads carrying out the simulation. The idle threads would report to the second kernel, B, which would have them generate and upkeep a pool of random numbers. The pool of random numbers would be used by the threads in kernel A, effectively reducing the amount of time the simulation would take as the time needed for getting a random number would simply be its selection from a pre-populated array. The threads in kernel B would keep the array filled with fresh random numbers until the simulations in kernel A had completed.

Before the CUDA framework had matured, those who required random numbers in their CUDA kernels had to develop their own method (Preis et al., 2009). The current CUDA framework includes a tool-kit for PRNG called "cuRAND" which includes many popular PRNG algorithms. In more recent iterations of cuRAND, the Mersenne Twister algorithm has been introduced which has become almost a de facto standard for PRNG (NVIDIA Corporation, 2010). However, its characteristic long period and large state size (Matsumoto and Nishimura, 1998) created difficulties when porting the algorithm over to GPGPUs. This is because GPGPUs work best with lightweight instructions and more complex PRNGs can reduce

performance. The default PRNG in cuRAND is the XORWOW algorithm, created by Marsaglia (2003).

Nandapalan et al. (2011) performs a study comparing the different PRNG algorithms available for GPGPU use. The focus is on the default cuRAND PRNG, XORWOW and the Mersenne Twister algorithm. Their findings were that XORWOW was more lightweight with a smaller footprint than the Mersenne Twister. In terms of throughput (random numbers generated per second), XORWOW had better performance than the Mersenne Twister algorithm. Finally, the quality of the random numbers generated was tested in the TestU01 Library which the authors state is a standard PRNG benchmarking suite. In this battery of testing, the Mersenne Twister failed two of the tests and the XORWOW algorithm failed three of the tests. Overall, the default cuRAND PRNG, XORWOW, seems to be better in situations where speed and lightness of weight are required. In problems where the quality of the random numbers is paramount, the Mersenne Twister algorithm is still recommended.

7.5 GPGPU-Optimised Algorithm for Petri-Net (PN) Simulation

Although there are studies in which PNs have been accelerated with GPGPUs, there are no examples in literature of asset management PN models being accelerated with GPGPUs. These represent a different challenge for GPGPU acceleration due to their increased complexity using advanced transitions with decision making capabilities. Additionally, there is evidence that GPGPUs are not able to accelerate all types of problems with the main issues being: (1) highly branched applications, (2) applications with large amounts of data causing memory latency mismatches and (3) imbalanced workloads as would be experienced with MC-based PN samples

(Che et al., 2013; Lee et al., 2010).

Designing a PN simulation algorithm to take advantage of the benefits of GPGPUs, but avoid the pitfalls, can be complex. The GPGPU PN algorithm which has been developed can be seen in Figure 7.7. The algorithm begins with creating the data on the host device, in this case containing the information to form the PN. Due to the CUDA framework being built on the C language, a common way of containerising the data is to use a structure-of-arrays or an array-of-structures, depending on the data access type of the problem.

The movement of data from the host to the device (stage 3 of Figure 7.7) can be wasteful as during this time, no computation is being carried out. Therefore, minimisation of the data being transferred can help with the computation time. In the context of PNs, each thread requires the complete set of data to construct the PN. This can be an expensive process as the same set of data would have to be moved to the device for each thread. However, the "constant memory" bank of the device was utilised which has the advantage of being able to distribute the data to the threads much quicker. Therefore, with PNs, it is beneficial to hold the structure of the PN in constant memory so that each thread can access that base information quickly, whilst holding the individual MC sample data within the threads individual memory.

Launching the kernel (stage 4 of Figure 7.7) involves setting the launch parameters, a combination of blocks and threads. The way the parameters are configured changes how the GPGPU processes the work. For example, if 1000 samples were required, one approach may be to consider each thread in its own block and then creating a launch configuration with 1000 blocks each with 1 thread. However, this approach is often the slowest configuration as with so many blocks opening and closing, the majority of the time is spent performing housekeeping on the device. The next most common approach is to launch as few blocks at once with the maximum

number of threads, in this example the configuration would be 1 block with 1000 threads. The thread-centric approach is faster than the block-centric approach but still suffers from low computational efficiency. Often the best launch configuration occurs when the threads have enough to compute to mask the opening/closing overhead, but not too much that they get bogged down with computation. This will often be problem specific, however it was found for the Tesla K40 used in this research that a product of blocks and threads that equalled 15,360 resulted in the quickest computation. This happens to be equal to the 15 SMX cores found in the Tesla K40 multiplied by 1024, the maximum number of threads which can be launched in a kernel.

Step 5 of Figure 7.7 mentions the thread ID check. This is an important step to avoid a thread trying to access elements of an array which do not exist. This step is required because: (1) threads are launched in groups of 32 known as warps, (2) all threads in a warp execute the same instructions and (3) the CUDA framework uses the C language where arrays are a popular container type. Therefore, if 1000 threads were requested, the GPGPU would launch the nearest multiple of 32 threads that satisfies the users request, in this case 1024 threads. The excess 24 threads would try to execute the same instructions as the rest of the warp, however if their was any attempt at reading from or write to an array which had a size of 1000, there would be an error. Therefore, it is very common in CUDA kernels to implement a thread ID check where any threads whose ID was greater than 1000 would be ignored.

The parallel execution seen in Figure 7.7 represents the PN sample simulations being executed on the GPGPU. Each of these simulations would carry out the same set of processes as seen in stages 4 through 10 of Figure 7.1. However, one of the most important aspects when designing an algorithm for GPGPU acceleration is to keep the code as lightweight as possible. Therefore, it was necessary to reduce the number of PN functions

to minimise branching. For instance, if a PN were to contain two types of transition: (1) those which move with a fixed time period and (2) those which are stochastic; it is beneficial to convert them to a single type that yields similar results. For example, in the railway bridge model, the carefully calibrated stochastic transitions were prioritised over standard fixed time transitions. The fixed time transitions were converted to stochastic transitions with a similar behaviour. Performing this operation speeds up computation because it avoids an IF statement for each transition, avoiding branching occurrences whilst maintaining similar model behaviour.

Step 8 of Figure 7.7 represents the aggregation of the results. This too can be GPGPU accelerated with the help of the Thrust library (NVIDIA Corporation, 2012). The Thrust library does not allow interaction with kernels directly, however it includes some built in functions which are very useful for PN simulations. One of the most useful is the reduce function which takes an array of any length and then finds the average. It uses the massively parallel characteristics of the GPGPU to quickly find the average value.

7.6 Simple Petri-Net (PN) Example

As a proof of concept, the simulations of a simple PN were accelerated using a GPGPU. The PN can be seen in Figure 7.8; it contains two places, two transitions and a token. The PN represents an asset failing and then being repaired. The transition marked "S" is a stochastic transition and models the failing of an asset represented by a probabilistic distribution. A fixed time transition is used to represent repair of the asset. In this example, the stochastic transition was calibrated with the exponential distribution with a lambda value of 0.035. The fixed time transition represented an instant repair. The sample was simulated for the equivalent of 100 years. The number of samples ($1 \cdot 10^8$) was chosen to provide enough time for the

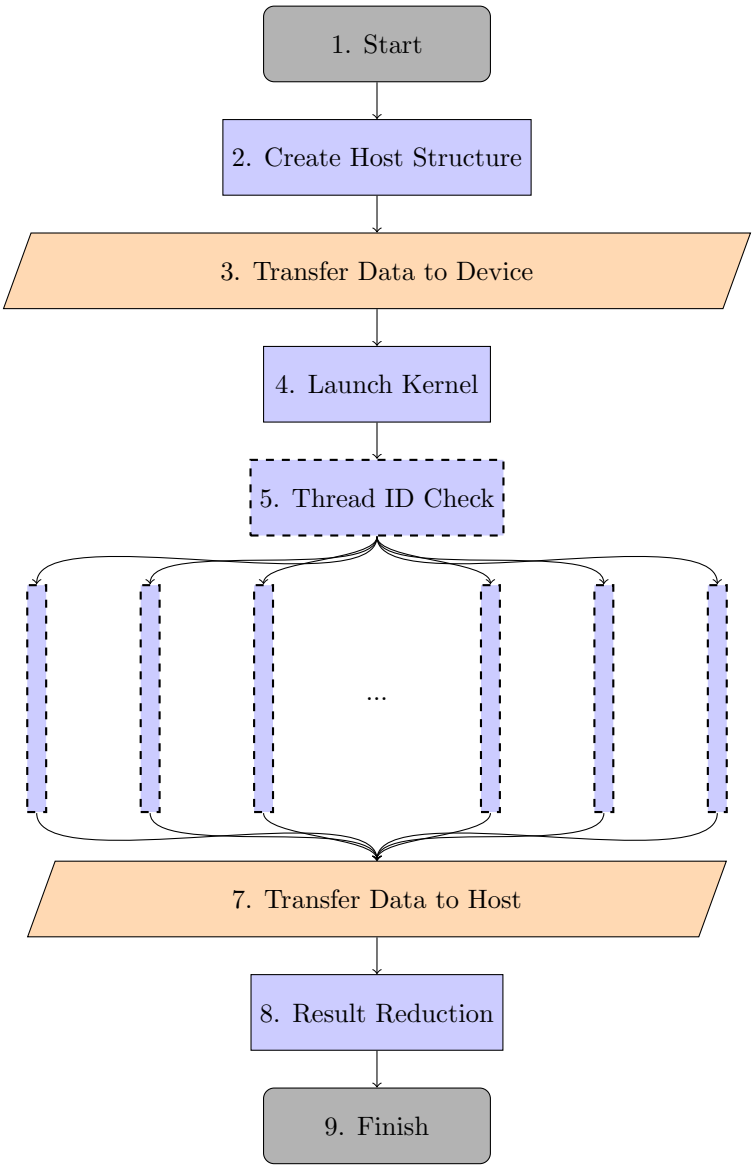


Figure 7.7: A schematic demonstrating how a PN algorithm could be devised for GPGPU execution. Nodes with solid outlines are performed on the host. Nodes with dashed outlines are performed on the device.

processing units to stabilise in their clock speeds.

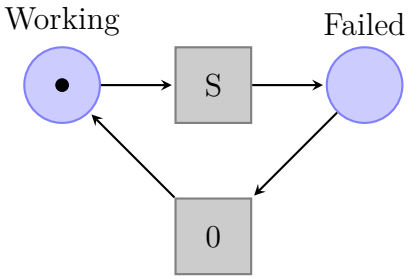


Figure 7.8: A simple PN accelerated with a GPGPU as a proof of concept .

The results of the analysis can be seen in Table 7.2. ID A1 shows the results of the PN simulated on a single CPU core. For this research a standard quad core desktop CPU was used. The time taken for a single CPU core was 12.89 seconds. This was measured using the C++ standard library timing functions. Using OpenMP (Dagum and Enon, 1998) allows for the simulation to be executed on all four cores of the CPU. This reduced the compute time to 4.481 seconds; just under a 3 times speed-up factor (ID A2). The parallelisation across multiple cores is not directly related to the single core performance, this is because there are overheads in opening, closing and controlling multiple threads.

As mentioned in section 7.4.2, the individual cores of a GPU are not as robust as a single CPU core. Therefore, when computed on a single GPU core (ID A3) the execution time was 237.8 seconds; almost 20 times slower than with the single core CPU performance. However, when all the GPU cores were enabled (ID A4) the time reduced to 0.085 seconds; over 150 times faster than the single core CPU performance. This result demonstrates the performance gains possible when simulating PNs on GPGPUs.

Table 7.2: Results of the execution time of a simple PN when computing on various devices.

ID	Device	Cores	Time (s)	Speed-up Factor
A1	CPU	1	12.89	1.00
A2	CPU	4	4.481	2.87
A3	GPU	1	237.8	0.05
A4	GPU	2880	0.085	152

7.7 Railway Bridge Petri-Net (PN) model

The railway bridge PN model is to be executed on the GPGPU to ascertain if acceleration is possible with such a complex model. The full model contains 76 places, 108 transitions of which 36 contain advanced decision making functions. A simplified overview of the model can be seen in Figure 4.2. The details of the full model can be found in Chapter 4. The full model (M_1) was modified to make it as lightweight as possible taking into consideration all the suggestions from section 7.5. This is required because single GPU threads are not as powerful as their CPU counterparts (see section 7.4.3). Therefore, if the full model (M_1) was executed on the GPGPU, the speed of execution would have been much slower and the advantages of using the GPGPU lost. The surrogate model (M_2) has a much smaller footprint and is more suited to GPGPU computation.

7.7.1 Comparison of Model Features

Table 7.3 details the major similarities and differences between the two models. One of the most important parts of both the full and surrogate models is the deterioration module. This module is identical in both models to ensure the same deterioration behaviour. The industry guidelines on inspection of railway structures (Network Rail, 2010d) are the same in both models. Once an inspection has taken place, if a repair was required, then the appropriate maintenance action would be selected. The industry guide-

lines on maintenance actions are the same in both models. The full model includes a number of advanced maintenance management features which complicates the PN. This has an adverse effect on the computation time as more features inevitably means more IF statements in the code which creates occurrences of branching. Therefore, in the optimised model these have been simplified to reduce the branching behaviour. For example, the Maintenance Decision Module of the full model includes both the industry standard guidelines (Network Rail, 2012a) as well as defect misdiagnosis, introduced in Chapter 6. Misdiagnoses of defects were implemented in the full model using probabilistic transitions however, these types of transitions introduce a significant amount of branching behaviour. Therefore, in the optimised model, the Maintenance Decision Module does not include misdiagnoses but still conforms to the industry standard guidelines. Additionally, variability in costs have been removed from the surrogate model to reduce branching behaviour. Overall, the surrogate model has a similar behaviour to the full model. However, due to the differences in the models features, the results are not exactly the same between M_1 and M_2.

Finally, the full model features detailed simulation outputs as seen in Section 4.3. The surrogate model is not able to produce such detailed simulation outputs. This is because GPUs feature a number of different memory banks and to access the fastest memory requires holding the most minimal amount of data. Therefore, by holding more detailed simulation records, the GPGPU threads would have had to use the slower memory which would have slowed the simulation results considerably.

7.7.2 Results of Model Simulations

The surrogate model was tested on both a CPU and GPU to compare the difference in time. The results can be seen in Table 7.4. The models were both run with $1 \cdot 10^6$ samples, fewer than was used with the first example as

Table 7.3: Comparison of the model features included in the full and streamlined railway bridge models.

Model Features	M_1	M_2
Historically Calibrated Deterioration	Yes	Yes
Industry Guideline Inspections	Yes	Yes
Industry Guideline Maintenance	Yes	Yes
Defect Misdiagnoses	Yes	No
Imperfect Repair	Yes	Yes
Variable Costs	Yes	No
Detailed Simulation Results	Yes	No

these models are more complex and therefore take longer to compute. ID B1 presents the results of the full model being simulated on a single core of the CPU which took a total of 16.51 seconds for execution. It can be seen that with multi-core execution (ID B2) the speed-up factor is similar to that found in Table 7.2 (ID A2). Result B3 again shows a significant slow down in single core GPU performance compares to A1, single core CPU performance. However, when comparing A4 and B4 it can be seen that there is a significant difference in the speed up factor, this is because of the sizeable difference in the amount of data needed to construct the PNs. Even though a process of data condensing was carried out in scenario B4, the data must be available for every thread which means that the overall execution time is much slower due to the data transfer process. With model M_2, profiling revealed that it was common for the data transfer process to take much longer than the actual compute time; this emphasises the importance of keeping the code and data as lightweight as possible. Overall, the results show that complex PN models can be simulated rapidly using GPGPUs.

7.8 GPGPU Acceleration Conclusion

PNs are becoming increasingly popular in the field of Asset Management (Andrews and Moss, 2002). However, it is common for these types of

Table 7.4: Results of the execution time of a complex PN when computing on various devices.

ID	Model	Cores	Time (s)	Speed-up Factor
B1	M_1	1	16.51	1.00
B2	M_1	4	4.358	3.78
B3	M_2	1	263.0	0.06
B4	M_2	2880	0.886	18.6

models to require MC-based simulations which can result in long compute times. As modelling approaches grow in complexity, the compute time often follows that. However, with the advancements of GPUs outstripping those of CPUs, acceleration of MC-based simulations using GPGPUs is gaining in popularity. Additionally, as time goes on: (1) the development of the CUDA framework makes the features of GPGPUs more powerful and user-friendly, (2) the compute performance of GPUs improves and (3) the cost per FLOPS drops. These factors mean that the adoption of GPGPU acceleration should increase dramatically.

One of the main complexities when developing for GPGPUs is understanding the difference in the processing units from the traditional CPU to those of a GPU. Creating code which is lightweight to run, contains minimal data transfers and is parallel in nature has the greatest opportunity for significant acceleration. As GPGPU adoption grows, there is more of a push towards unification of the GPGPU and CPU compute units which will help to mask the boundaries between the host and the device, encouraging further adoption.

The purpose of this chapter was to identify whether acceleration of simulations of complex PN models would be suitable for GPGPUs with the specific example of the railway bridge PN model. The reason that this was investigated was that it was recognised that trying to perform decision optimisation with the full model may be computationally infeasible. Therefore, this investigation was designed to see if GPGPU acceleration was feasible

for accelerating complex PN models so that optimisation would not be so computationally expensive. To that effect, a simple PN was used as a proof of concept with a single stochastic transition. This simple PN was designed to mimic a basic asset from a working to failed state. Acceleration of this PN resulted in over a 150 times speed-up factor from serial CPU execution.

The chapter then focused on the acceleration of the railway bridge PN model. The model contains a number of advanced decision making transitions, associated with Coloured Petri-Nets (CPNs). A streamlining exercise was performed on this model to make it more suitable for GPGPU execution, the details of which were documented in Section 7.5. When the accelerated code was profiled, it became apparent that the data transfer from the host to the device was taking the majority of the time; emphasising the importance of minimising data transfers. The final result was that the railway bridge PN model was accelerated to almost 20 times its original speed. This enhances the practicality of this approach for decision support tools for bridge portfolio managers and improves the chances of adoption.

The next chapter will detail how the GPGPU acceleration can be used for rapid decision optimisation results. This should allow much easier adoption of the model as a tool to support decision making as the time penalties associated with the model would be much lower.

Chapter 8

Inspection Procedure Optimisation

It has been established in Chapter 5 that the environment can greatly affect the deterioration profile of railway bridge elements. Therefore, for agencies responsible for these types of structures, implementing an effective management policy is paramount. This chapter investigates the optimisation of the inspection regimes to reduce the Whole Life-Cycle Costing (WLCC) whilst maintaining a healthy population of bridges.

Current UK industry guidelines do not account for these environmental influences. In this chapter, the railway bridge Petri-Net (PN) model is combined with Local Environmental Factors (LEFs) and system uncertainty to provide a comprehensive model that will be used to optimise decisions. One of the drawbacks of sophisticated models is the increased computational cost. This is even more severe when the model is used as part of the optimisation framework. To mitigate this, this chapter details a novel optimisation framework based on a Hybrid Genetic Algorithm (GA) approach which uses two stages: (1) a rapid General-Purpose Graphics Processing Unit (GPGPU) based surrogate model to accelerate evolution of the population into the region of interest and then (2) using those in-

dividuals as seeds for the full model for the final honing procedure. This should provide good optimised results with all the advantages of the fully featured model, but without the associated time delay.

According to the latest public expenditure report from Network Rail (NR), over £551m is spend annually on their population of bridges (Network Rail, 2015). Therefore, there is a significant potential benefit by performing optimisation on their inspection regimes.

8.1 Review of Optimisation with Bridge Asset Management Models

A number of studies have been undertaken to optimise the management of bridges. Various approaches have been used ranging from dynamic programming (Frangopol and Liu, 2007) to shuffled leap-frog optimisation (Elbeltagi et al., 2007) and even testing all possible combinations to comprehensively check the search space (Estes and Frangopol, 1999). However, the vast majority of the studies use GAs (Sørensen, 2002; Miyamoto et al., 2000; Elbehairy et al., 2006).

Konak et al. (2006) and Frangopol (2011), amongst others, mention that with reliability and asset management problems, often there are multiple objectives which are conflicting. For example, trying to minimise WLCC on its own will inherently cause a minimisation of the number of interventions which can create safety issues. However, trying to maximise the condition of the asset over its lifetime will cause budgetary issues. One approach is to try to convert the objectives into a single objective problem using constraints and weighted factors. However, the issue with this approach is that the management of assets can be complex and therefore trying to assign weightings can be subjective and introduce a great amount of uncertainty (Liu and Frangopol, 2005). These studies state that using a

Multi-Objective Genetic Algorithm (MOGA) is more appropriate. Not only are conversion factors avoided, but the outputs of a MOGA contain a greater depth of detail about the objective functions and therefore are more suitable to make decisions with (Frangopol, 2011).

Liu et al. (1997) was one of the first studies that tried to perform management optimisation of bridge decks. The authors state that most of the previous studies had focused on minimising costs however this can have negative impacts on the condition of the structures, which increases risk for bridge portfolio managers. They propose using MOGAs with both fitness sharing and Pareto optimality ranking. The model is based on a non-linear deterioration module as well as a rehabilitation module which improves the condition of the bridge decks. Only major rehabilitation is considered in this study. The Pareto optimality ranking is used to create classes of solutions in different cost categories; allowing bridge portfolio managers to choose an appropriate action based on their budgetary capability. This approach is applied to the 287 bridges of Nagoya City, Japan. They compare the MOGAs approach to a random search approach. In the comparison of the techniques, the MOGA searched the space more effectively and so the Pareto Front was more extensive than that found with the random search technique.

Miyamoto et al. (2000) also perform a study on the optimisation of bridge rehabilitation. Their model relates deterioration to the load carrying capacity of the bridge. The authors optimise for both the minimum cost and maximum soundness score, a measure of deterioration, over a 100 year period. This study also compares GAs to another approach, this time the branch-and-bound method. They state that both methods are able to provide similar results in terms of costs, however the GA approach was more successful as it provided a more comprehensive optimal maintenance plan.

Neves et al. (2006a,b) perform an interesting set of studies. Both studies try to optimise bridge maintenance strategies, however each study deals with a different scope for the interventions. In the first study, only rebuilds are available for rehabilitation. The authors use an established probabilistic model (Neves and Frangopol, 2005) to optimise the maintenance strategies. Latin Hypercube is used to increase the efficiency of the MOGA; it actively determines the event outcomes to maximises the search space. This study optimises three parameters: (1) minimisation of the cumulative cost, (2) maximises the condition of the bridge and (3) minimise the safety index. An interesting result was that if the rebuild is scheduled earlier in the deterioration process, the impact to the individual elements is less significant. However, this introduces issues with both the cumulative cost and safety index. An additional study was performed which analysed the effect of applying silane, a preventative maintenance action. Silane reduces the absorption of chlorides which slows the deterioration of concrete structures. Two factors were introduced which were the year of initial silane coating and the interval of subsequent coatings.

The second study that Neves et al. (2006b) perform involves combining both the rebuild and silane interventions. The reason for this is that silane on its own is not able to improve the condition, only to slow the deterioration. Additionally, the authors state that of the interventions available to bridge profile mangers, only the rebuild is safety-orientated. They state that the goal of the optimisation is to find the best time for the initial silane coating, the interval of the subsequent coatings and if a rebuild is necessary. For this they use the same MOGA to optimise cost, condition and safety. The authors discuss that the results can be split into two main groups; (1) those where rebuild was not required and only silane was used, similar to the results of their previous study (Neves et al., 2006a), and (2) those where rebuild was required. They mention that this created a discontinuous Pareto front and those where rebuild was included resulted in

much higher condition and safety indices, which was expected. The authors identify that breaching the safety threshold has a more severe impact than breaching the condition threshold. For this reason they re-run their study trying to minimise the number of safety breaches. The authors mention that there was a large variation in the optimised strategies across their studies. With the single maintenance action scenario, they mention this would result in a simpler maintenance schedule, however does not result in as good performance in terms of the objectives. The multiple maintenance action scenario gives a more tailored schedule resulting in better performance, but results in a more complex schedule.

The majority of the studies investigate the best time to perform maintenance, however, Orcesi and Frangopol (2011) performs a study to try to work out the best pattern for inspections. They say that there are two outcomes for inspections: (1) no defect is found and therefore no maintenance is required or (2) a defect is found and the appropriate maintenance action is scheduled. If no defect is found, the probabilistic deterioration profile is updated according to the event-tree. For this they use a MOGA and minimise both the inspection and maintenance costs as well as the failure costs. They use the Non Sorting Genetic Algorithm II (NSGAII) to make the process more efficient. They conclude that using MOGAs is an effective way of creating an inspection regime that minimises both the amount of inspections and the costs of bridge failure.

Table 8.1 shows the main parameters used in studies discussed earlier. Even though the majority of these studies only optimise 2 parameters, the diversity of both the size of the population and the number of generations required shows the complexity of this task. The downside to this method is that it is often computationally expensive, resulting in long execution times (Elbehairy et al., 2006).

Table 8.1: Summary of the main GA parameters used in literature for the optimisation of bridge maintenance.

Study	Population	Generations
Liu et al. (1997) (1)	300	50
Liu et al. (1997) (2)	500	100
Miyamoto et al. (2000)	30	300
Liu and Frangopol (2005)	1000	40
Elbehairy et al. (2006)	100	500
Neves et al. (2006a) (1)	100	5
Neves et al. (2006a) (2)	100	20
Neves et al. (2006b) (1)	200	20
Neves et al. (2006b) (2)	500	40
Orcesi and Frangopol (2011)	75	200

8.2 Genetic Algorithms (GAs)

GAs, created by Holland (1973, 1975) have become very popular for solving complex optimisation problems. They have had significant adoption in Engineering, Finance and Physics (Jones et al., 2002). The reason they excel in complex optimisation problems is that they: (1) do not require as much information about the problem compared to previous gradient-based optimisation approaches (Neves et al., 2006a), (2) the optimisation process is carried out on the encoding rather than the problem itself (Konak et al., 2006) and (3) they use a population of possible solutions to more thoroughly check the search space (Liu et al., 1997).

The first step in GAs is defining the problem characteristics including the objective function. The objective function is used to determine if one solution is superior to another. The solution in this regard is the fitness of an individual. Each individual contains its own set of variables, known as chromosomes. An initial population of individuals is generated and each individual is processed to evaluate their specific fitness. The individuals are then ranked and those which score highly are retained for the next generation. The best individuals are used to produce offspring to occupy some of the remaining spaces. Mutated individuals are also generated in the

population to increase the diversity of the population. The new population will then be processed to evaluate the fitness of the individuals with only the fittest individuals remaining. This process continues for a number of generations until satisfactory optimised solutions are obtained (Holland, 1973).

8.3 Multi-Objective Genetic Algorithms (MOGAs)

A common addition to GAs is the use of MOGAs (Goldberg and Deb, 1991). The most common problem involves multiple, often conflicting, objectives. In this instance, the fitness of each individual is reported as multiple values e.g. overall cost and average condition. The conflict in this example is that trying to increase average condition often conflicts with minimising costs. The major difference between GA and MOGA is that with a single objective, there will be an individual who is fittest. However, when considering multiple objectives there is a trade-off between the objectives and so all of the optimal solutions are of the same fittest rank. This provides the user with a range of outputs across their parameters from which they can choose the best one for their situation; this is known as the Pareto optimal set (Deb, 2001). Together these individuals make up the Pareto front which can be graphically plotted to provide the user with an understanding of the optimal set of solutions for their problem. The NSGAII has become a very popular algorithm for MOGAs due to its ability to scope out the Pareto front (Deb et al., 2002). This is possible due to its avoidance of crowding which means that individuals are more likely to be in unexplored areas of the search space (Konak et al., 2006). Due to these advantages, NSGAII has been used in this research.

8.3.1 Multi-Objective Genetic Algorithm (MOGA) Implementation

Implementation of MOGAs can be carried out in a number of ways. The method opted for in this research was a C++ implementation because of its compatibility with the Compute Unified Device Architecture (CUDA) framework, which has been discussed in Section 7.4.3.1. A number of C++ MOGA libraries were available, but the most developed and feature-rich seemed to be OpenBEAGLE (Gagné and Parizeau, 2006). This library is optimised for both efficiency and flexibility making it ideally suited for this application. An interesting feature of OpenBEAGLE is that it is designed to support Parallel GAs. This uses multiple populations, known as demes, where each of the demes resides in the vivarium. Depending on the configuration of the GA, it is possible to move individuals between demes each generations. This can help stop population stagnation. The additional advantage of this feature is that multiple isolated demes can be evolved to check if the global maximum/minimum has been achieved (Alba and Troya, 1999).

8.3.2 Parallel Genetic Algorithms (GAs)

GAs use a population of individuals which allows the search space to be checked more thoroughly than other optimisation methods (Franconi and Jennison, 1997). This characteristic has a downside though; maintaining a population of individuals can be computationally expensive as the fitness function must be executed frequently. As models improve over time, this often leads to increased model sophistication causing longer execution times. A number of studies have been performed to parallelize GAs. Parallel GAs are advantageous for two reasons: (1) the structured nature of the populations, or demes, allows for more efficient evolution and (2) the algorithm lends itself well to being executed on multi-core systems to speed up

the execution time. Alba and Troya (1999) state that in nature, evolution is often in small groups and not global; therefore, the use of demes and a vivarium is closer to real-world evolution. The authors' suggested methods for structuring the demes are: (1) the island method, (2) the diffusion grid and (3) stepping stones. The authors mention that more communication between demes jeopardises the scalability of the method, hence the greater adoption of the course-grained approaches that have less communication. The authors conclude that parallel GAs are ideally suited to complex problems with heavy fitness functions.

Cantú-Paz (1998) introduces the most basic parallel GA variety known as the "single population master-slave" model. This essentially treats the population as a whole and processes multiple individuals at once depending on the computational capability. The authors state that the greatest gains in efficiency occur when the number of processing units matches the individuals in the population. If this were to occur the time taken for each generation would be similar to the time taken to process a single individual.

In the context of the railway bridge model, a number of Monte Carlo (MC) samples are required to ascertain the behaviour of the PN model. This means that during optimisation, each individual must be simulated for a certain number of samples. This adds another layer of possible parallelisation as seen in Figure 8.1. As well as each individual being able to be parallelized, each of the samples within each individual can be parallelized too. This could be particularly powerful on clustered machines where different types of processing units are available to create a tiered hierarchy (Maulik et al., 2011). In a perfect system, where the number of compute units exceeded the number of samples across the individuals, the time to perform one generation would be similar to the time taken to execute one sample; a significant speed-up.

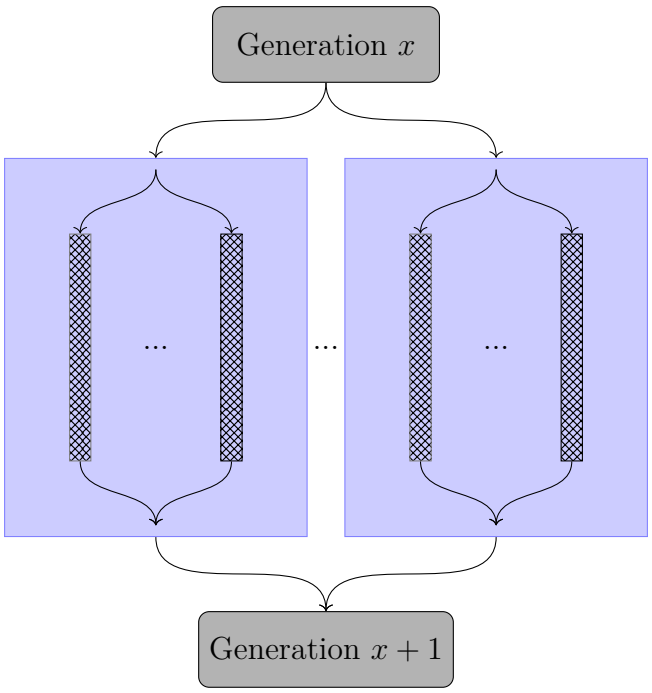


Figure 8.1: A schematic demonstrating how a GA could be parallelized for stochastic PNs.

8.4 Hybrid Genetic Algorithm (GA) Approach

A number of studies have used Hybrid GA approaches (Nain and Deb, 2002; Nair et al., 1998), but they often switch to a different technique for the second phase (e.g. Artificial Neural Networks) (Poloni et al., 2000).

Using the full railway bridge PN model (M_1) as the base, a surrogate model (M_2) was developed. M_2 was developed keeping in mind the limitations of GPGPUs. M_2 yields results similar to M_1, but when combined with the use of a GPGPU, a speed up in computation of almost 20 times can be achieved (see Section 7.7). Therefore, a hybrid approach has been proposed. Using the faster M_2 model will provide a coarser optimisation where the majority of the model features are considered but not all. The evolved population can then be used as the starting population to seed the full model, M_1 for the fine adjustment. An example of how this works is shown in Figure 8.2.

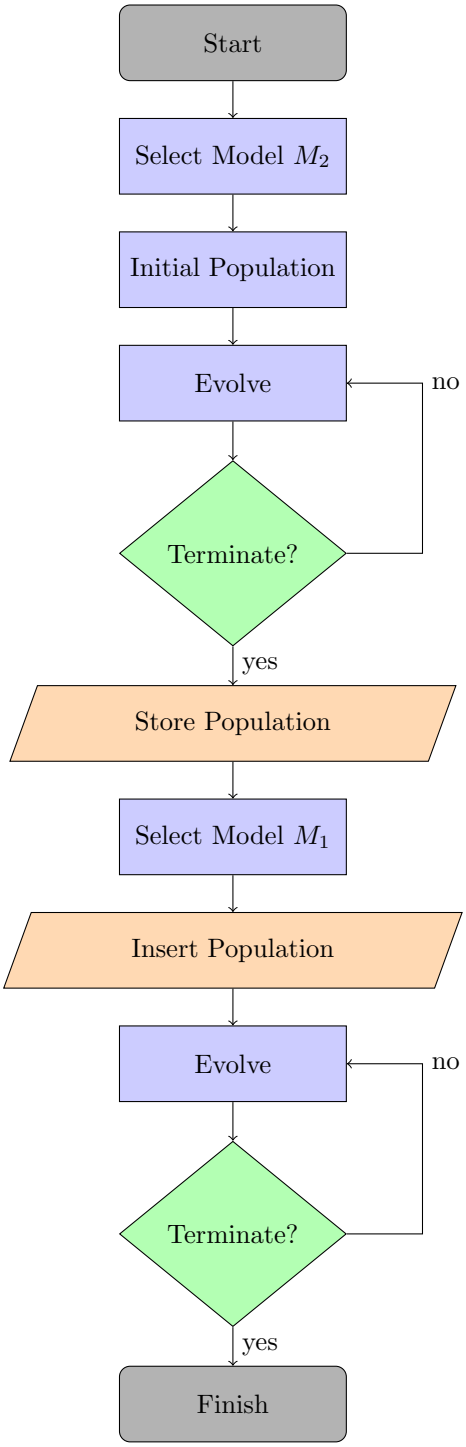


Figure 8.2: Flow diagram explaining the Hybrid GA approach.

8.4.1 Objective Functions

In this research, optimisation is carried out to minimise both the WLCC and the probability of the bridge elements being in a condition requiring Replacement. This is carried out by altering the inspection intervals of the bridge elements in the advanced transitions of the inspection module (see Section 4.1.3). Advice from the industry suggested that changes to the inspection policies would be well received whereas changes to the maintenance policies could have far reaching implications which limits their adoption.

8.4.1.1 Full Model Objective Functions

For the full model, the first objective is to minimise the WLCC of the elements over the simulation period (100 years), as seen in Equation 8.1.

$$WLCC = \sum_{i=1}^{N} \left(\sum_{j=1}^{n_1^i} c_{1,j}^i + \sum_{j=1}^{n_2^i} c_{2,j}^i + \sum_{j=1}^{n_3^i} c_{3,j}^i + \sum_{j=1}^{n_4^i} c_{4,j}^i \right) \tag{8.1}$$

where N is the total number of bridge components, n_1^i is the number of Inspections of bridge component i, n_2^i is the number of Minor Repairs of bridge component i, n_3^i is the number of Major Repairs of bridge component i, n_4^i is the number of Replacements of bridge component i, $c_{1,j}^i$ is the array of Inspection costs for bridge component i, $c_{2,j}^i$ is the array of Minor Repair costs for bridge component i, $c_{3,j}^i$ is the array of Major Repair costs for bridge component i and $c_{4,j}^i$ is the array of Replacement costs for bridge component i.

Using industry guidelines (Network Rail, 2010c), the maintenance actions are related to the condition of the element, as would be expected. Below the "Basic Safety Limit" there is a recognised safety issue and the elements are replaced as a matter of urgency. This is something that bridge portfolio managers want to avoid as there are severe operational, budgetary and service implications. In this research, a condition at or below the Basic

Safety Limit is considered a condition where a Replacement intervention is required. Therefore, the second objective function is to minimise the probability of the elements being in a condition requiring Replacement; this can be seen in Equation 8.2. The way this is achieved is to consider all the element conditions which are at or below the Basic Safety Limit and the time the element resides in those conditions.

$$C = \sum_{i=1}^{N} \left(\frac{t^i_{D6} + t^i_{E5} + \cdots + t^i_{G6}}{N \cdot T} \right) \tag{8.2}$$

where N is the total number of bridge components, T is the total simulation time, t^i_{D6} is the time bridge component i resides in condition state $D6$.

8.4.1.2 Surrogate Model Objective Functions

The WLCC objective function of the surrogate model differs from that of the full model because it uses average costs for inspection and maintenance. The reason for this is that it reduces branching behaviour which, in turn, increases computational throughput.

$$WLCC = \sum_{i=1}^{N} \left(n^i_1 \cdot c^j_1 + n^i_2 \cdot c^j_2 + n^i_3 \cdot c^j_3 + n^i_4 \cdot c^j_4 \right) \tag{8.3}$$

where N is the total number of bridge components, n^i_1 is the number of Inspections of bridge component i, n^i_2 is the number of Minor Repairs of bridge component i, n^i_3 is the number of Major Repairs of bridge component i, n^i_4 is the number of Replacements of bridge component i, c^j_1 is the average cost of Inspections of bridge component type j, c^j_2 is the average cost of Minor Repairs of bridge component type j, c^j_3 is the average cost of Major Repairs of bridge component type j, c^j_4 is the average cost of Replacements of bridge component type j.

The surrogate model uses the same objective function for the probability of the elements being in a condition requiring Replacement. Both the full

model and surrogate model are implemented in OpenBEAGLE with the NSGAII algorithm to increase efficiency.

8.4.1.3 Genetic Algorithm (GA) Migration Functions

Although a whole host of selection techniques are available for GAs, tournament selection was decided upon because of its ability to be highly effective in a parallelized architecture (Coello et al., 2007). The decision to use binary tournament selection (i.e. tournaments of 2 individuals) was made because it has a low loss of diversity and keeps the selection variance high, which were considered important benefits (Goldberg and Deb, 1991).

To perform the crossover functions, single point uniform crossover was chosen with an exchange probability of 0.5. This seems to be a popular choice due to its consistent performance (Spears and De Jong, 1990).

Finally, a uniform mutation function was chosen with a probability of 0.05. This seems like a popular chosen value to stop the population from converging on a sub-optimal point too quickly, but without excessively randomising the search (Srinivas and Patnaik, 1994; Goldberg and Holland, 1988; Grefenstette, 1986).

8.4.2 Populations, Demes and Generations

8.4.2.1 Parallel Genetic Algorithms (GAs)

Often, when using GAs, the size of the population and the number of generations is problem specific. A number of studies have been performed using MOGAs on bridge asset management models which give a broad envelope into an appropriate population size and number of generations. Additionally, when using GPGPU accelerated GAs, the execution time can be significantly faster, so it is possible to test a variety of configurations to work out which is the best for the problem. For example, a number of studies mentioned that using parallel GAs, where multiple demes are

used, could improve the Pareto front. This is because each deme would start in a different area of the search space. In addition, migration between demes would keep diversity high. Therefore, testing the number of demes and comparing the Pareto front should ascertain the suitability of this approach with this problem. For this the M_2 model was used with a baseline population size of 100 individuals.

A summary of the configurations can be seen in Table 8.2. The baseline scenario (ID 1) used a single deme of 100 individuals over a maximum of 100 generations. The next scenarios (ID2-ID4) have an increase in the number of demes and a proportional decrease in the number of generations to keep the computation smilar. Within each generation, 5 individuals were moved between the demes randomly, in conformance with Parallel GAs. This should show the suitability of using Parallel GAs with this particular problem. ID5 was also included to maximise the potential benefit of Parallel GAs by increasing the number of demes to 10 and reducing the number of generations to 10. It was considered that fewer than 10 generations would limit the evolution of the individuals.

Table 8.2: Configurations of the populations, demes and generations when testing the suitability of Parallel GAs.

ID	Demes	Generations	Individuals Migrating Per Generation	Execution Time
1	1	100	N/A	11m,31s
2	2	50	5	11m,50s
3	3	33	5	12m,06s
4	4	25	5	11m,51s
5	10	10	5	12m,49s

Figure 8.3 shows the results of the Parallel GA tests. The y-axis shows the WLCC of a main girder element over 100 years and the x-axis shows the probability of requiring replacement over the 100 year simulation period. By comparing the extents of the Pareto fronts, it is possible to see if this technique offers any advantage in this problem. Multiple demes with

migration should allow for greater diversity, maximising the search space, leading to a superior Pareto front. If this had occurred, then the Pareto front of ID5 should be superior to the Pareto front of ID 1. However, there is no significant difference in the extents of the Pareto fronts between ID1 and ID5. This suggests that, for this problem, Parallel GAs is not effective.

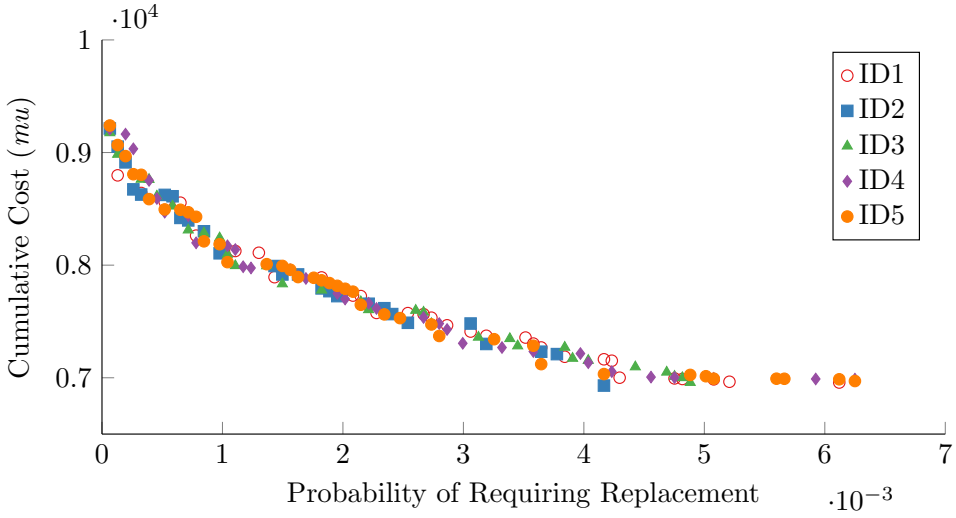


Figure 8.3: Pareto fronts showing the suitability of Parallel GAs.

8.4.2.2 Population Size

The general thoughts on population size for GAs is that too small a population will result in a lack of diversity and therefore achieving the global optimum is unlikely. On the other hand, a large population will keep the diversity high, avoiding genetic stagnation, however may result in inefficient use of resources and unsatisfactory solve time (Haupt, 2000). Roeva et al. (2013) carries out a study on the optimal population size for a problem with three model parameters. They test population sizes from 5 to 200. With each population size they compare the average fitness of the individuals across 200 generations. The results suggest that smaller population sizes do not perform as well as larger population sizes. However, beyond a population size of 100, the average fitness score seems to start

to increase. The authors conclude with a statement that larger population sizes may not offer any advantage and simply take more time and resources to compute.

Konak et al. (2006) mentions that with the use of NSGAII, the population size is even more important because of the way that the algorithm is designed. This is because non-dominated solutions are included in the next generation with the remaining spaces allocated via their crowding characteristic. It is the crowding characteristic which sets NSGAII apart from other techniques and is particularly important for maximising the Pareto front.

There is evidence to suggest that testing different population sizes may be beneficial for this problem in terms of solution performance and computational time; especially considering the complexity of the problem and the inclusion of NSGAII. Considering both the literature discussing population size (Chen et al., 2012; Roeva et al., 2013; Haupt, 2000) and the literature specifically on optimisation of bridge maintenance (Liu et al., 1997; Liu and Frangopol, 2005; Neves et al., 2006a), a variety of different population sizes were tested with a fixed number of 100 generations. For this comparison, the M_2 model was used due to its computational efficiency. Table 8.3 shows a summary of the analysis. A population size of 200 individuals seems like a good compromise between both objective functions and the execution time.

8.4.2.3 Stopping Criteria

A number of studies have investigated the stopping criteria for GAs. Using MOGAs complicates the issue further as all the objectives need to be considered. Rudenko and Schoenauer (2004) carried out a study into the stopping criteria for MOGAs. The authors propose a stability measure to estimate the probability of a superior individual being found. The method hooks into the NSGAII algorithm to work out how well the population

Table 8.3: Summary of testing with different population sizes.

Population Size	Average Fitness		Execution Time (h:m:s)
	WLCC (mu)	Probability of Requiring Replacement (10^{-3})	
50	8028	1.98	00:06:07
100	7758	2.29	00:11:41
150	7685	2.76	00:17:54
200	7670	2.55	00:23:21
250	7747	3.02	00:30:18
300	7775	2.12	00:36:22
500	7840	2.20	00:58:15
1000	8535	0.65	02:06:11

is progressing towards the Pareto front. They state that as the population progresses towards the Pareto front, the number of Pareto ranks decreases. However, even when the whole population has progressed to the same Pareto rank, fitness improvements can still be achieved, therefore it is not an effective stopping criteria. The authors propose a measure of stability which relies on crowding function built into NSGAII. The measure compares the maximal crowding distance of the current generation to the maximal crowding distance of all the generations. When the stability measure goes below a set threshold, then the appropriate moment to stop the MOGA has been found. Although the authors give advice on how to choose a suitable threshold, they also recognise that if an incorrect threshold is selected, the MOGA may stop at an inappropriate time, limiting the effectiveness of this approach.

Marti et al. (2009) also proposes a MOGA stopping criteria. The approach includes the MGBM criterion which was developed previously by the same authors (Marti et al., 2007). By adding the mutual domination rate and applying a basic Kalman filter, the authors state that they can estimate the progression of the optimisation. Their approach compares the local improvement to the global evidence to suggest an appropriate time

to stop the GA. The authors apply their approach to three test problems; they conclude that their approach is able to detect the generation at which to stop more quickly than other techniques tested. However, they identify their approach may be triggered prematurely if a large proportion of the population is non-dominated.

The most common stopping criteria for a MOGA is simply to choose a fixed value. The literature examined in Section 8.1 all seem to use a fixed value for the maximum number of generations based on trial and error with their specific problem. This method seems simpler, more intuitive and more robust. Vrajitoru (2000) argues that a larger population may be more beneficial than a large number of generations and that there is an optimum balance between the two. In Section 8.4.2.2, it was found that a population of 200 individuals seems to be best for this problem. A further test was carried out to see what corresponding number of generations should be selected. For this test the M_2 model was used with a comparison of the populations and the execution time.

Figure 8.4 shows the fitness of the individuals grouped by their generation. The initial population, identified as generation "0", is quite scattered as would be expected. It can be seen that, in general, as the generations mature, the population progresses towards the Pareto front. The population which has evolved 100 generations seems to be slightly improved over that of 50 generations and the same as that which has evolved 200 generations. Even though 100 generations takes almost twice as long as 50 generations, 00h:23m:21s compared to 00h:12m:44s, it was selected due to the improved performance.

The maximum number of generations has so far been tested on the surrogate model due to its efficiency. However, as explained in Section 8.4, a Hybrid GA approach is being employed in this research to find near-optimal solutions quickly and then use a fine-grained approach for the final stage. Therefore, a transition in the evolution must occur between the two stages.

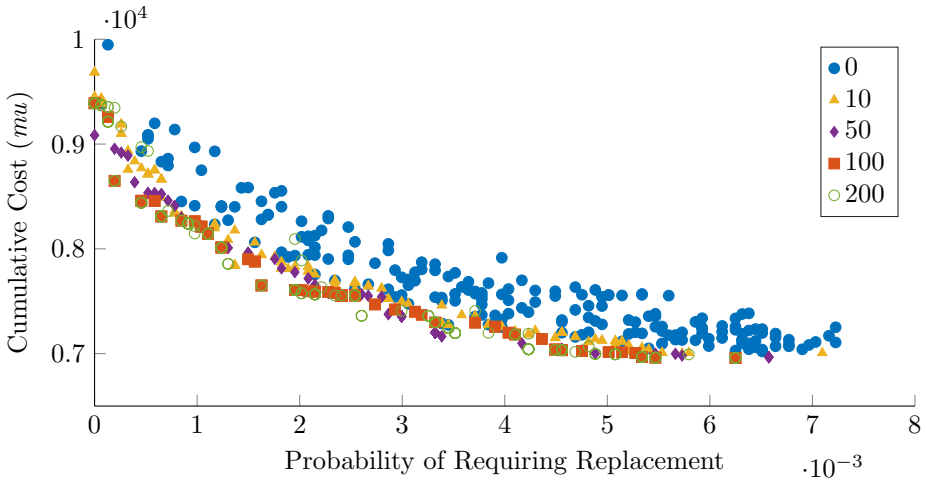


Figure 8.4: A comparison of the development of the non-dominated individuals within each generation.

Poloni et al. (2000) compared a number of different Hybrid GA approaches. In their comparison, they use 36 calls to the approximation technique to 1 call of the full algorithm. Although the optimisation was not carried out on a bridge management problem, their approach provides a baseline for the transition between the models. It was determined in the previous section that 100 generations seemed to provide a good balance between performance and computation time. Therefore, the stopping criteria for the complete Hybrid GA process is set at 100 generations. The surrogate model will perform the first 97 generations at which point the GA will transition to the full railway bridge model to hone the final 3 generations.

8.4.3 Computational Speed Comparison

A Hybrid GA is being used in this research because it should drastically reduce the typical times for MOGAs. The first part of the Hybrid GA is a surrogate, GPGPU accelerated model, used to find the general region of optimality. The second part is a fine grained GA, used to hone the Pareto front and the find the optimal individuals.

To increase efficiency, there is evidence to suggest that for simple PN

models, using an importance sampling technique can be beneficial (Nicola et al., 1993). However, the Coloured Petri-Net (CPN) approach used in the model combines continuous and discrete transition probability distributions in a complex arrangement. Although the use of Latin Hypercube Sampling has been used successfully in bridge asset management (Neves et al., 2006a), when subjected to high dimensionality the performance of the sampling technique quickly degrades to a similar performance as the MC approach (Owen, A., 2013). The model used in this research contains over 70 dimensions which would negate the advantage of using such a method. Therefore, for this research, the standard MC approach was used.

The first section of the Hybrid GA, using surrogate model, was executed using GPGPU acceleration whilst the second section, using the full model, uses the Central Processing Unit (CPU).

To compare the difference in speed of each part, a population of 200 individuals was optimised in each of the GA sections. The control scenario was used for this test. The device used in this research is a single Tesla K40. Modern desktop computers are able to hold up to 4 of these devices and use them concurrently which means that there is even greater opportunity for speed improvements.

Table 8.4 shows the difference between the parts. The time reported is the time to process one generation. The difference in speed between the two parts is significant with the GPGPU accelerated part performing the calculations on an entire generation in 14.44 seconds, representing over a 800x speed-up over the fine grained GA. These results show that the Hybrid GA approach has significant scope for accelerating traditional MOGAs.

To perform the full Hybrid GA takes approximately: (1) 0.5 hours for the first stage using the coarse GPGPU accelerated surrogate model and then (2) 10 hours for the three generations to be optimised using the fine grained full model. Using the Hybrid GA approach represents a 30x speed-up over the traditional approach where only a single model is used.

Table 8.4: Comparison of the coarse and fine grained GA approaches used in this research to create the Hybrid GA approach. The "time" refers to the time taken to process one generation of 200 individuals.

Part	Model	Device	Time (h:m:s.ms)	Relative Time
1	Surrogate	GPGPU	00:00:14.44	1.24×10^{-3}
2	Full	CPU	03:14:23.34	1

8.4.4 Optimisation Problem Definition

By using the streamlined GA to test various GA parameters and features, a more comprehensive understanding of the problem is gained. For example, finding the optimal population size with ones problem can be found much more readily because of the rapid results gained from using the GPGPU accelerated GA. This means that the final optimisation problem can also be better defined which should benefit the final results.

The motivation for using Genetic Algorithms for this problem is because: 1) GAs excel in highly nonlinear problems, such as the one being considered in this chapter, because they use a population of individuals to concurrently explore the search space and find areas of optimality (Jones et al., 2002), 2) they require less information about the problem than gradient-based techniques (Neves et al., 2006a) which means they require less configuration as they work on the encoding rather than the problem itself (Konak et al., 2006) and 3) GAs have become almost a de facto standard for optimising structural modelling problems (Frangopol, 2011).

Table 8.5 gives the details of the formal definition of the optimisation problem. The industry guidelines explain that three separate values are used for the inspection frequency of bridge elements (see Section 2.2.3.7). The inspection frequency is decided upon based on the condition of the element. For example, with the standard NR inspection policies, an element that was in a condition which would require Major Repair would be inspected every 6 years (72 months). The chromosomes of the individuals in

the optimisation procedure directly map to these three values. The values are embedded into the Inspection Module seen in Figure 4.7. An individual calibrated with the standard NR inspection policies would have the following genes: 144, 72, 36 which are the durations in months from Table 2.4. The upper and lower bounds for each of the genes (1 - 240 months) have been agreed upon through discussion with industry experts.

8.5 Optimisation Results

The results of the optimisation are presented both in tabular form and as a series of Pareto Fronts. Each LEF has been processed through the Hybrid GA optimisation to provide optimised individuals for each one.

Figure 8.5 shows the results of the optimisation with the deterioration calibrated to the control scenario (ID1). This includes the concrete bridge girder elements in all LEFs. Shown in the figure is the Pareto Front as produced by the Hybrid GA approach, as well as the fitness of an individual calibrated with the standard NR policies. The figure has been divided into quadrants based around the fitness of the individual calibrated with the standard NR policies. In the figure, individuals residing in quadrants III and IV represent individuals calibrated with inspection policies which are cheaper over the 100 year simulation period than the individual calibrated with the standard NR policies. Individuals in quadrants I and III represent individuals calibrated with policies which have a lower probability of requiring replacement than individual calibrated with the standard NR policies. Therefore, individuals that reside in quadrant III represent individuals calibrated with policies which are both cheaper and have a lower probability of requiring replacement than the individual calibrated with the standard NR policies, which shows that the standard NR inspection policies are sub-optimal.

The probability of requiring replacement is a direct metric of condition,

Table 8.5: Summary of the optimisation problem and associated parameters.

Main Objectives	1) Minimise WLCC	2) Minimise probability of the element being in a condition requiring Replacement
Objective Functions	$f_{1,M1} = \sum_{i=1}^{N} \left(\sum_{j=1}^{n_1^i} c_{1,j}^i + \sum_{j=1}^{n_2^i} c_{2,j}^i + \sum_{j=1}^{n_3^i} c_{3,j}^i + \sum_{j=1}^{n_4^i} c_{4,j}^i \right)$ $f_{1,M2} = \sum_{i=1}^{N} \left(n_1^i \cdot c_1^j + n_2^i \cdot c_2^j + n_3^i \cdot c_3^j + n_4^i \cdot c_4^j \right)$ $f_2 = \sum_{i=1}^{N} \left(\frac{t_{D6}^i + t_{E5}^i + \cdots + t_{G6}^i}{N \cdot T} \right)$	
Chromosones	Gene 1 Gene 2 Gene 3	Inspection Frequency (months) for elements in a condition which would require Minor Repair Inspection Frequency (months) for elements in a condition which would require Major Repair Inspection Frequency (months) for elements in a condition which would require Replacement
Constraints	Gene 1 Gene 2 Gene 3	1 - 240 1 - 240 1 - 240
Total options	Gene 1 Gene 2 Gene 3	240 240 240
Population Size		200
Stopping Criteria		Fixed Generations
Generations		M2: 97 M1: 3
MOGA Technique		NSGAII
Selection		Binary Tournament
Crossover		Single Point Uniform, $P_c = 0.5$
Mutation		Uniform, $P_m = 0.05$

but is also an indirect measurement of risk. This is because the threshold for replacement is calibrated to the NR "Basic Safety Limit" which represents their appetite for risk.

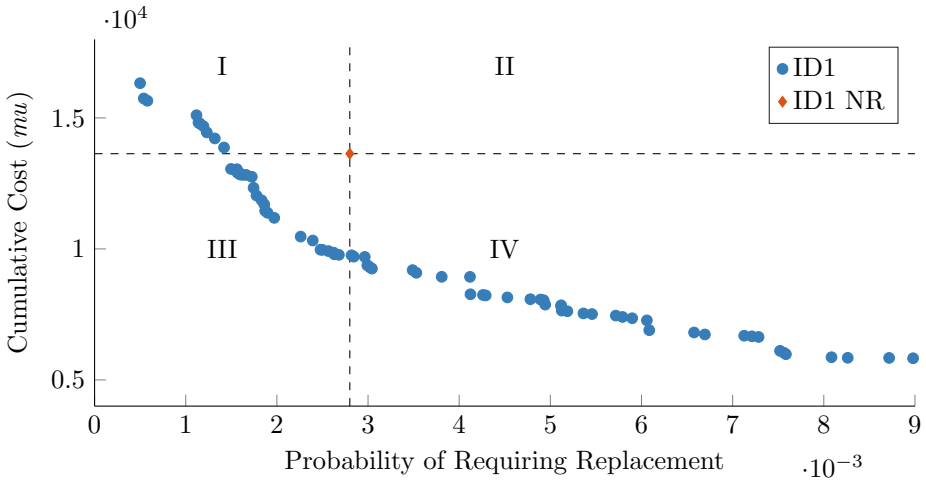


Figure 8.5: Results of the optimisation with the control scenario (ID1).

Figure 8.6 shows the results of the optimisation with the two main structure types: overline (ID2) and underline (ID3) bridges. Although these categories do not cover the entirety of the portfolio, they do consider >90% of the population of bridge assets across NR's portfolio. Overline bridges carry the roadway over the railway and the results of the optimisation show that they are cheaper to manage across the whole range of individuals. Underline bridges, which carry the trains over the roadway are subjected to increased rates of deterioration. For this reason they are both more expensive and have a higher probability of requiring replacement than overline bridge elements.

Figure 8.7 shows the result of the optimisation with the coastal scenario LEFs. Bridge elements closer than 5Km to the coast (ID4) experience rapid deterioration. This is evident because their cumulative cost seems to dominate the other scenarios with a much higher probability of requiring replacement. Bridge elements which are between 5 to 25Km from the coast (ID5) seem to experience deterioration rates worse than the control

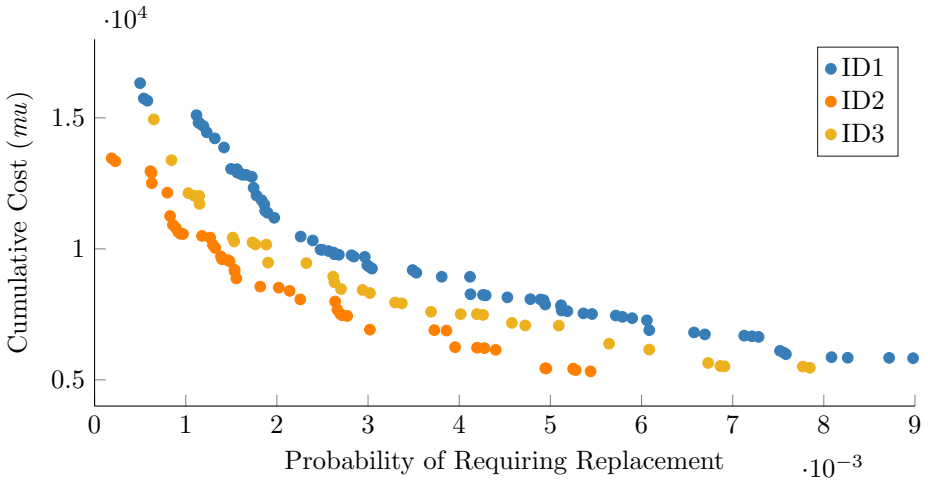


Figure 8.6: Results of the optimisation comparing Overline (ID2) and Underline (ID3) Bridge elements to the control scenario (ID1).

scenario but not as severe as ID4. Bridge elements in this category are at a reasonably high probability of requiring replacement. Finally, bridge elements which are greater than 25Km (ID6) from the coast experience much milder deterioration rates. Bridge elements in this category cost less than the control scenario and have a lower probability of requiring replacement.

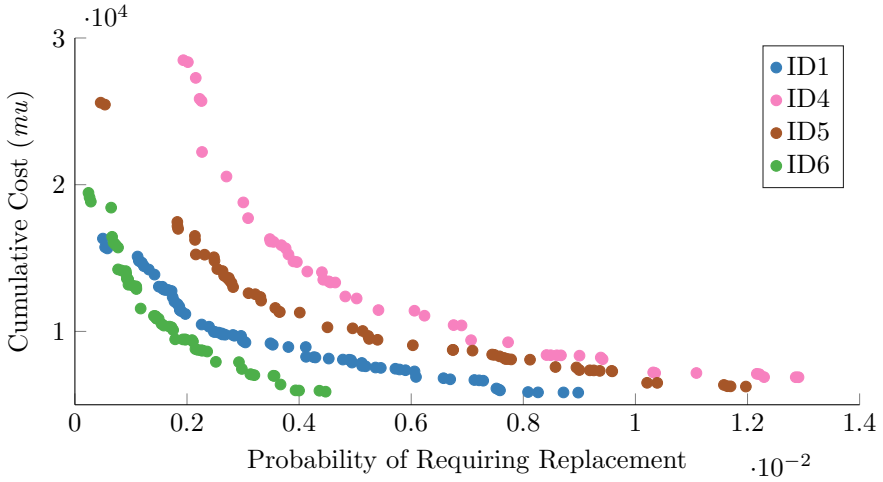


Figure 8.7: Results of the optimisation comparing bridge elements within 5Km to the coast (ID4), 5-25Km from the coast (ID5) and those which are greater than 25Km (ID6) to the control scenario (ID1).

Figure 8.8 shows the results of the optimisation with the different severities of galvanic corrosion. The galvanic corrosion categories are in reference to a study which identified the rates of galvanic response across the UK (UK Galvanizers Association, UK Galvanizers and High Chemicals UK Ltd., 2002). Starting with ID7, which represents bridge elements in areas of mild galvanic corrosion, it can be seen that they are much less expensive than the control scenario (ID1) and carry less risk. This is represented by the fact that they have a much lower probability of entering a condition state that would require replacement. Those in moderate areas of galvanic corrosion (ID8) seem to be roughly in line with the control scenario. Finally, ID9 represents bridge elements found in areas with the highest corrosion rates. These elements seem to be the most severely affected as they carry a very large risk of entering a state requiring replacement. Additionally, the cumulative cost seems to dwarf the other scenarios including the control scenario. It can even be seen that ID9 is more severe than ID4 from Figure 8.7, demonstrating that a bridge element in an area of high galvanic corrosion costs more and is more at risk that one closer than 5km to the sea.

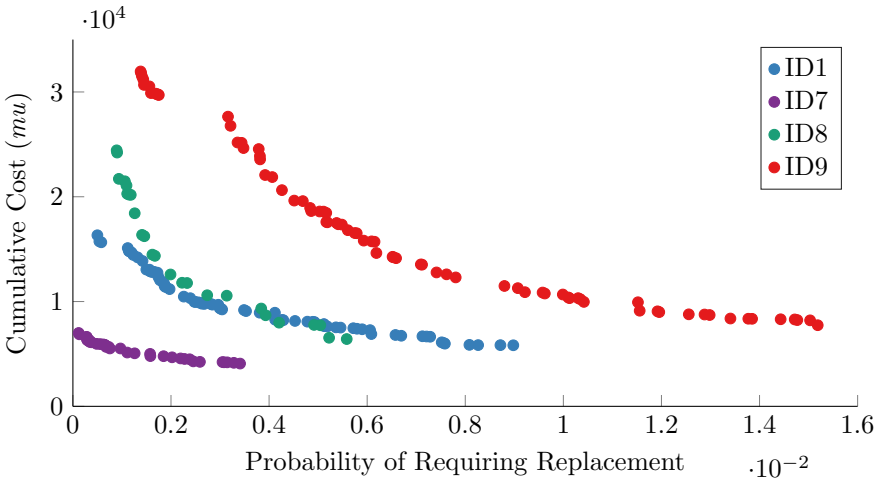


Figure 8.8: Results of the optimisation comparing bridge elements in areas of mild galvanic corrosion (ID7), moderate galvanic corrosion (ID8) and high galvanic corrosion (ID9) to the control scenario (ID1).

The significant difference evident in Figures 8.7 and 8.8 stems from the disparity between the environmental stressors, which concurs with the results found in Section 5.5. This is aggregated by the fact that elements which deteriorate at a faster rate are more likely to be towards the centre of the Severity Extent Rating (SevEx) matrix upon inspection, and so a misdiagnoses of the element defect is higher (see Table 6.1) which leads to a higher probability of the incorrect maintenance action being scheduled (see Section 6.2.1). Therefore, assets which are exposed to more severe stressors are more likely to have an incorrect maintenance action scheduled, which further delays appropriate remedial action and increases their overall WLCC. Hence the disparity between IDs 4,5,6 and IDs 7,8,9 is significant in Figures 8.7 and 8.8.

The fitness of the optimised individuals for each LEF can be used in comparison to the fitness of the individual calibrated with the standard NR policies exposed to the same LEF. The fitness of the individual calibrated with the standard NR policies, given as the WLCC and the probability of requiring Replacement, can then be directly compared with the individuals produced from the Hybrid GA approach. The most straightforward comparisons are 1) comparing the individual with the closest WLCC to the individual calibrated with the standard NR policies within each LEF and 2) comparing the individual with the closest probability of requiring Replacement to the individual calibrated with the standard NR policies within each LEF. For example, in Figure 8.5, the two non-dominated individuals which lie closest to each of the dashed lines could be directly compared to the individual calibrated with the standard NR policies. These would allow direct comparison of policies which are 1) very close in WLCC or 2) very close in the probability of requiring Replacement.

Tables 8.6 and 8.7 present this comparison. Table 8.6 presents the closest individual in terms of the WLCC and Table 8.7 presents the closest individual in terms of the probability of Requiring Replacement. When

considering the individuals in Table 8.6, it can be seen that in most cases, for the same WLCC as the individuals calibrated with the standard NR inspection policies, a lower probability of Requiring Replacement is achieved. In general, the frequency of inspections seems to match the severity of the deterioration within each LEF scenario ID, for example, when looking at IDs 7,8,9 it can be seen that as the severity of the LEF increases, the optimised inspection frequency is tighter. This suggests that with more severe LEFs, by having a more frequent inspection regime, which can be seen by the lower values in the genes, defects are found quicker and corrected more quickly, reducing the WLCC. Therefore, this approach seems to lower the overall WLCC by increasing the amount of inspections to detect defects early and reduce the expenditure on costly rehabilitations.

When considering the individuals in Table 8.7, it can be seen that in most cases, for the same probability of Requiring Replacement, a lower WLCC is achieved. By analysing the values in the genes, it can be seen that it is a more targeted approach than the standard NR inspection policies with more frequent inspections on elements in poorer conditions and less frequent inspections on elements in better condition.

Table 8.6: Comparison of the individuals calibrated with the standard NR inspection policies with the closest individuals calibrated with the optimised inspection policies in terms of the WLCC.

	Individual calibrated with the standard NR inspection policies					Individual calibrated with the optimised inspection policies				
	Chromosome (months)			Fitness		Chromosome (months)			Fitness	
ID	Gene 1	Gene 2	Gene 3	WLCC (nearest $100mu$)	Probability of Requiring Replacement	Gene 1	Gene 2	Gene 3	WLCC (nearest $100mu$)	Probability of Requiring Replacement
1	144	72	36	13700	0.003	73	62	40	13900	0.001
2	144	72	36	6200	0.001	240	123	112	6100	0.003
3	144	72	36	12000	0.004	57	34	17	12100	0.001
4	144	72	36	26000	0.006	48	32	30	25700	0.002
5	144	72	36	23600	0.005	50	20	6	25500	0.001
6	144	72	36	5800	0.002	240	179	28	5900	0.004
7	144	72	36	5200	0.002	120	71	44	5300	0.001
8	144	72	36	8000	0.003	124	52	40	7900	0.003
9	144	72	36	38800	0.008	24	20	12	32000	0.001

Table 8.7: Comparison of the individuals calibrated with the standard NR inspection policies with the closest individuals calibrated with the optimised inspection policies in terms of the probability of Requiring Replacement.

	Individual calibrated with the standard NR inspection policies					Individual calibrated with the optimised inspection policies				
	Chromosome (months)			Fitness		Chromosome (months)			Fitness	
ID	Gene 1	Gene 2	Gene 3	WLCC (nearest $100mu$)	Probability of Requiring Replacement	Gene 1	Gene 2	Gene 3	WLCC (nearest $100mu$)	Probability of Requiring Replacement
1	144	72	36	13700	0.003	124	92	56	9200	0.003
2	144	72	36	6200	0.001	240	108	98	9500	0.001
3	144	72	36	12000	0.004	205	163	32	7500	0.004
4	144	72	36	26000	0.006	128	78	32	11400	0.006
5	144	72	36	23600	0.005	176	127	124	10000	0.005
6	144	72	36	5800	0.002	154	96	33	7900	0.002
7	144	72	36	5200	0.002	171	120	38	4600	0.002
8	144	72	36	8000	0.003	124	52	40	8700	0.003
9	144	72	36	38800	0.008	107	41	28	12300	0.008

8.5.1 Discussion: Three Parameter Optimisation

The two parameters selected for optimisation in this research are: 1) WLCC and 2) the probability of requiring a replacement. However, there may be a better approach than using the WLCC. Some organisations may allocate a budget for inspections and another budget for maintenance, depending on their departmental organisation. Therefore, a similar Hybrid-GA approach can be used optimising for the following three parameters: 1) the cumulative cost of inspections, 2) the cumulative cost of maintenance and 3) the probability of requiring a replacement. The interest with this approach was that optimisation may suggest a solution where a budgetary re-balance would be recommended to put more emphasis on inspections/maintenance. A sample output can be seen in Figure 8.9. When consulting industry experts, they did not see any advantage of this approach for their own organisations, however it has been included in this chapter as an alternative for other organisations.

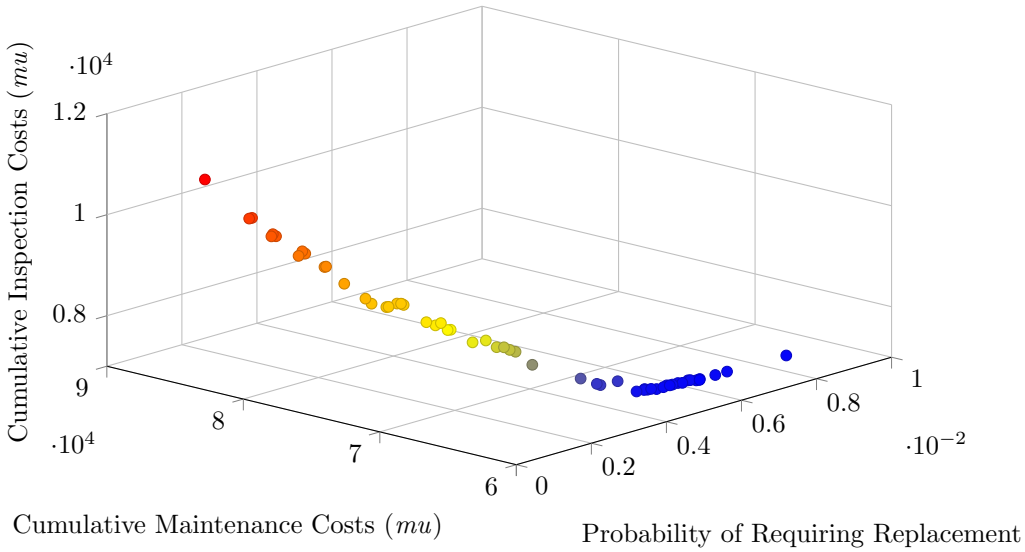


Figure 8.9: Sample optimisation result with the control scenario when considering three parameters.

8.6 Optimising Inspection for UK Bridges

8.6.1 Financial Comparison

The available data contains information for over 74,000 concrete girder elements within the UK. The number of girder elements exposed to each LEF are shown in Table 5.1. Additionally, the dominant LEFs have been identified in Table 5.5. Therefore, by using this information, it is possible to ascertain how much the groups of girders in each LEF scenario are costing in terms of the WLCC over 100 years. Using the fitness of the individuals calibrated with the standard NR policies, the total WLCC expenditure on all the girders over 100 years is 1037Mmu. These calculations can be carried out with the optimised results from the Hybrid GA process. In each LEF scenario, the non-dominated individual was chosen which had the closest probability of requiring Replacement to that of the individual calibrated with the standard NR policies. This individual was selected so that there would be little or no change to the probability of requiring Replacement with the standard NR policies. The results show that when using the optimised policies, the total WLCC expenditure on all the girder elements is reduced to 939Mmu, which is a 9.5% reduction.

To be able to implement these results, the industry standard policies for bridge inspections would have to be updated. Once inspections were being carried out to the new regime, then the corresponding savings in WLCC are possible. Overall, these results show that a significant reduction in WLCC is possible for railway portfolio managers by simply modifying their current inspection procedures.

8.6.2 Bridge Condition Comparison

An alternative to using the results to reduce the portfolio WLCC would be to use the results to improve the condition of the overall portfolio.

A comparison of the fitness of the optimised individuals was carried out against the fitness of the individual calibrated with the standard NR policy within each LEF. The policy was selected from the fittest non-dominated individual which most closely matched the WLCC fitness of the individual calibrated with the standard NR policy and compared accordingly.

Figure 8.10 shows a map of the UK which has been divided into a grid. Each grid square has been analysed to determine which LEF would be dominant in that area. This is to show what a bridge in each location would be subjected to. By comparing the WLCC of the optimised policies to the WLCC of the standard NR policy, the improvement in the probability of requiring Replacement can be calculated. It can be seen that across the majority of the UK a significant improvement in the probability of requiring Replacement is possible. Areas which experience rapid deterioration, close to the coast or in areas of high galvanic response, have less scope for improvement and so their potential uplift in the probability of requiring Replacement is lower.

8.6.3 Performance-Based Inspection Planning (PBIP)

Another approach to interpreting the results is to analyse the inspection costs in each LEF scenario. Different environmental scenarios lead to better or worse deterioration rates so there is evidence to suggest that inspection efforts should be calibrated accordingly. The results in Section 8.5 suggests that bridges subjected to more severe LEFs will experience greater rates of deterioration and therefore it is advisable to implement a more rigorous inspection regime. For example, increase the inspection frequency and therefore, inspection expenditure, on bridges that are at risk of more rapidly deteriorating, identified by their LEF category, with the incentive that defects are caught earlier and so are easier and less expensive to repair. Conversely, bridges that experience milder deterioration may not need to

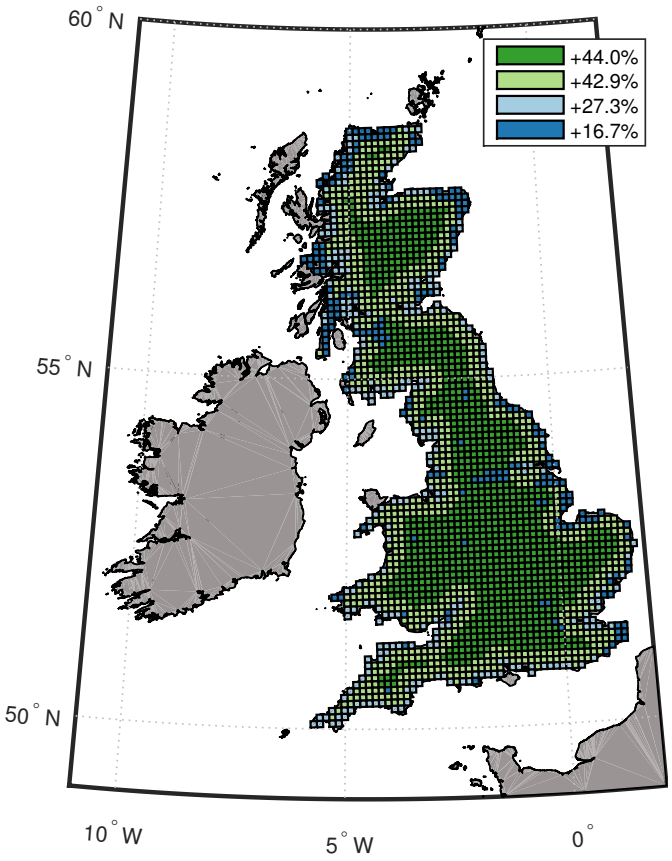


Figure 8.10: Map of Great Britain showing the relative improvement in the probability of requiring Replacement between the optimised policies and the NR standard policy for the same cost.

be inspected as often.

To that effect, a Performance-Based Inspection Planning (PBIP) protocol is proposed. The "performance" in this regard is the probability of requiring Replacement as experienced within the LEF scenario. By implementing the PBIP protocol, budget efficiency is increased as it allows more focus to be put on assets which require greater monitoring and less focus on those that do not. Different areas are subjected to different LEFs and therefore the inspection costs of an asset in that area will also vary.

Figure 8.11 shows a map of the UK split into the same grid as Figure 8.10. An optimised policy which has the same probability of requiring Replacement as that of the standard NR policy has been selected. The

inspection costs of the chosen optimised policy have been compared to the inspection costs of the standard NR policy. Although not every square contains a bridge asset, the purpose of this map is to identify what the increase/decrease in inspection costs of an asset in that area would be according to the PBIP protocol. The results show that in areas subjected to high galvanic corrosion or which are close to the sea, the inspection costs can rise as much as 29%. With a greater number of inspections on the appropriate assets, defects can more quickly be detected and corrected, reducing costly rehabilitation works. Fortunately, for the vast majority of the UK, the inspection costs drop more than 7% by using the PBIP protocol.

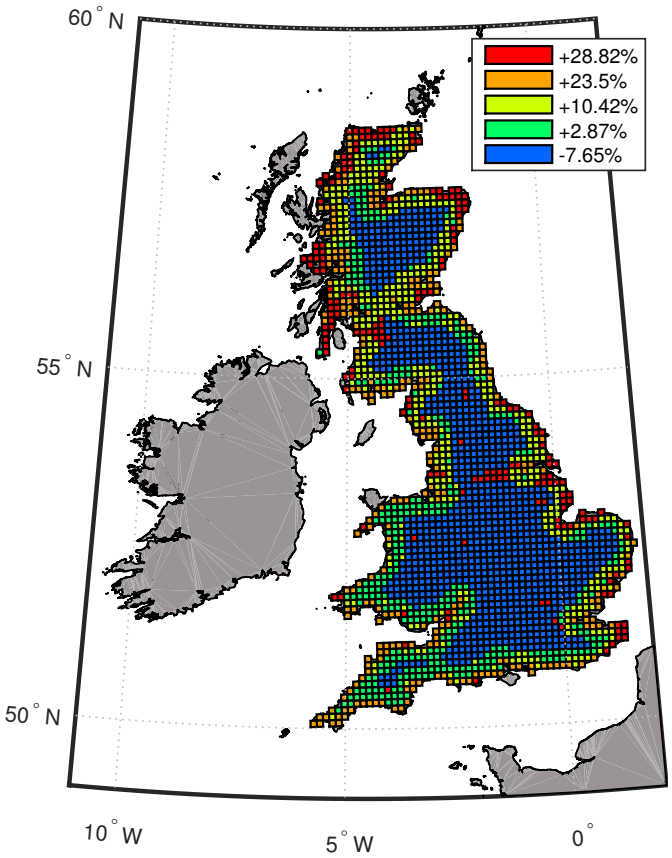


Figure 8.11: Map of Great Britain showing inspection cost increases/decreases compared to the standard NR policies.

There is strong evidence that by using the PBIP protocol budgetary

efficiency is improved. Not only would defects be caught earlier on higher risk assets, reducing the overall maintenance costs, but across the majority of the UK fewer inspections are required. In addition, because fewer inspections are required in the majority of the UK it reduces portfolio-level inspection costs and allows maintenance teams to focus on assets which need closer monitoring.

8.7 Optimisation Conclusion

Optimisation of policies for bridge management has been the topic of a number of studies (Frangopol, 2011; Neves et al., 2006b; Liu et al., 1997). This research pushes forward that goal, but incorporates a number of additional features. This begins with the railway bridge PN model which includes a plethora of advanced decision making capabilities to make the model more true-to-life that would not be possible with traditional modelling approaches. It was identified that using such a complex model to perform optimisation would not be efficient and so a surrogate model was developed that could be rapidly evolved using GPGPUs. The surrogate model provides good comparative, repeatable performance that evolves the population of individuals to the region of interest. It performs each generation over 800 times faster than full model. Then the full model is able to hone the final results of the optimisation. Together the surrogate model and the full model provide a new Hybrid GA approach which works to optimise at over 30 times the speed of a conventional GA approach.

The results of the optimisation have been focused on UK railway bridges. With this data, a map of the UK has been produced which show where condition improvements would be possible considering the environmental stressors in each area. A novel inspection-based performance protocol has been created to show where railway bridge managers should focus their efforts in terms of inspections. This is based on the dominant LEFs in each

area which determines whether a bridge at that location would be subjected to more or less severe deterioration and therefore the corresponding inspection efforts associated with that. Additionally, a financial comparison was carried out between the current UK industry guidelines on inspections and the optimised inspection policies. It was calculated that the optimised policies were able to provide over a 9.5% reduction in the WLCC at the same bridge health condition. This is a notable result for bridge portfolio managers as the savings are significant and promise to do so with no greater risk than the existing policies.

Chapter 9

Conclusion

9.1 Summary of Conclusions

Management of a large portfolio of infrastructure assets is a complex and demanding task for transport agencies. For infrastructure portfolio managers, decision support tools are becoming increasingly more useful. The literature review revealed a number of Bridge Management Systems (BMSs) that have been produced to help support the decisions of bridge portfolio managers. This field was pioneered by Pontis and Brigit with notable contributions from KUBA. This research presents a new approach to BMSs using a number of new novel features including: 1) the move away from the traditional Markov approach to a new Petri-Net (PN) based modelling method which allowed inclusion of advanced decision making features to make the model more realistic, 2) full adoption of a Severity Extent Rating (SevEx) condition system which OMBS and Network Rail (NR) seemed to use initially, but then converted to a more basic system, 3) a thorough investigation into the factors affecting deterioration, which was touched upon by KUBA, 4) the flexibility to adapt to different industry policies and practices with minor changes like that featured in DanBRO and finally, 5) the ability to optimise the inspection intervals of bridge assets

to allow the minimisation of Whole Life-Cycle Costing (WLCC) and the minimisation of the probability of requiring Replacement. Overall, it can be seen that this research presents a new approach to BMSs that builds upon the best concepts from the existing BMSs and develops them further to provide a more modern and comprehensive approach to BMSs. This should provide greater detail and understanding to bridge portfolio managers to assist them in their decision making. Considering the original aim of the research was to develop a new approach for a decision support tool for bridge portfolio managers, this research has fulfilled that aim.

The model itself was one of the main focuses of the research. Identification of the main parts of the system was one of the most important initial stages of developing the approach e.g. understanding the evolution of defects, the impact of condition-based-inspections and the processes of rehabilitation. By combining the historical data with the industry policies and practices on inspection and maintenance, an overall understanding of the system was gained. The model is able to be simulated to supply outputs which provide key insights into the behaviour of the system over the lifetime of the structure; simply acquiring this perspective is useful for bridge portfolio managers.

The process of deterioration is one of the most important aspects of structural modelling and so an investigation into the factors that affect deterioration was carried out. This was made more difficult by the choice to use the 2-Dimensional condition rating system. Therefore, a new approach was developed to be able to compare and contrast the behaviour of two 2-Dimensional systems using a network analysis approach. This was used to determine if various environmental effects were or were not factors affecting deterioration. The key factors affecting deterioration, denoted as Local Environmental Factors (LEFs), were identified. However, it was recognised that in order to provide enough information for bridge portfolio managers, the financial impact of these LEFs would need to be known. Therefore, a

typical bridge element was simulated using the model, subjected to each of the LEFs individually, to provide comparative model outputs including the financial impact of the LEFs. This gives bridge portfolio mangers an important new insight into the factors which cause deterioration of their assets.

Variability in the industry practices was investigated to find possible sources and determine the effect of variability on the system. The sources of variability were determined to be: 1) the variability in inspections leading to misdiagnoses of defects, 2) variability in the costs of maintenance works and 3) variability in the quality of repair which lead to introducing imperfect repairs into the model. The effect of misdiagnoses had a direct impact on the WLCC as well as the condition of the structure, as misdiagnoses of the defect often lead to the incorrect type of maintenance being scheduled which increased the overall WLCC, but left the condition of the element in a worse state as often the works could not be carried out and would have to be rescheduled. When combining this with imperfect repairs, the condition of the element was often starting from a worse position after rehabilitation than with perfect repairs and therefore even more maintenance actions would have to be carried out over the lifetime of the structure, increasing the WLCC. Overall, it was deduced that replicating the variability seen in the real-world system increased the financial and operational demands of the structure. The results of this are useful for bridge portfolio managers as they can understand the sources of variability in their organisational practices and how much they affect their assets with a view of reducing the amount of variability.

Using the model to perform optimisation allowed for improved inspection policies to be provided. Improvement of inspection policies was focused upon as they would be easier for industry to adopt than safety/maintenance policy changes. The full PN model is computationally heavy to use in optimisation and so a lighter-weight model was developed to run on

General-Purpose Graphics Processing Units (GPGPUs) which greatly accelerated the model simulation time. This technique was developed into a novel Hybrid Genetic Algorithm (GA) approach which uses the lightweight GPGPU-based model to quickly find the area of interest and then use the fully featured model to perform the final generations to hone the individuals. This technique offers a great advantage as it allows for faster execution, which means decisions can be made more quickly and in addition enables "What-If" analysis to be performed, all of which improves its chances of adoption. Therefore, GPGPU acceleration is a useful feature for a BMS as it would be would more beneficial for decision making. Additionally, the optimised results which were produced from this research give a good insight into the types of financial and operational savings which are possible. For large organisations with expansive bridge portfolios, the approaches outlined in this research could enable them to both reduce the overall bridge portfolio expenditure and focus their inspections on specific bridges which are in areas of more severe LEFs using the Performance-Based Inspection Planning (PBIP).

The purpose of this research was to develop a new approach to BMSs which builds upon the strengths of the existing ones. What was identified was that flexibility to adapt to different organisations policies and practices was required, as well as the ability to accommodate the deterioration characteristics of their particular bridge stocks. A PN based modelling approach was chosen as it provided the required flexibility. Adding to the model was the factors affecting deterioration and variability. Finally, an optimisation procedure was developed which can provide rapid results to assist decision makers. Overall, it can be seen that the approach developed has introduced a number of both novel and useful features which should be able to benefit the bridge managers of tomorrow.

The advantages of using this approach in practice is that: 1) the model is much more flexible to possible changes in both maintenance and inspec-

tion policy, 2) the monthly time steps offer a much higher granularity than the yearly condition steps currently provided by the majority of BMSs, 3) the model itself has the ability to model interactions between elements on the same structure, which existing BMSs are often unable to perform, 4) the model is able to consider elements of bridges exposed to different stressors, which existing BMSs often neglect and finally, 5) the model is able to provide optimised inspection intervals to determine when is best to catch defects to minimise WLCC and the probability of requiring costly rehabilitation.

The disadvantages of using this system in practice is that: 1) it only considers the asset and sub-asset level and so there is no portfolio level modelling, 2) the data which was available was not of the quality required to be able to calculate lifetime distributions, 3) the probabilistic transitions used in the model means that it is more computationally expensive than the traditional Markov approach and 4) there is no commercially available software for processing Coloured Petri-Nets (CPNs) which means that a CPN simulator is required.

The results of this research allow bridge managers to directly improve how they are managing their bridges by: 1) indicating which environmental factors are affecting the deterioration of their assets and the impact of those stressors, which allows more targeted inspections of assets, 2) the sources of variability have been investigated so that bridge managers have an indication of the sources as well as the impact which allows them to focus on improving specific bridge management practices and finally 3) the optimisation approach demonstrated significant improvements in generating inspection policies which offer better average asset condition as well as lower WLCC. Overall, there are a number of benefits which this research has provided to allow bridge managers to improve on their existing management practices.

9.2 Contribution of Research

Throughout the course of this research, a number of key findings have emerged:

- **Adoption of the 2-Dimensional condition state system.** Adoption, calibration and use of the 2-Dimensional condition monitoring system is distinctive in asset management modelling. The 2-Dimensions tracks both the elements defect and the extent of that defect. The calibration involved using historic data ranging over 16 years. This feature is novel and has been mostly avoided in asset management due to the complexity of adoption however, was deemed an important feature of this research.

- **Identification of the key factors affecting deterioration.** A number of possible factors affecting deterioration were analysed. Those which were determined to be major causes of deterioration were identified and then ranked according to the financial impact they would have on railway bridge portfolio managers. This is a key finding of the research and is key to effective bridge management.

- **Development of the state-of-the-art.**The results of the research have contributed to the state of the art in the following ways: 1) by demonstrating a more flexible approach to WLCC modelling of railway bridges with the use of PNs and CPNs, 2) through the fast, low cost comparison technique which allows the comparison of 2-D condition matrices which avoids the use of factors or weights which can introduce subjectivity, 3) with the identification of the sources of variability in the management of railway bridges and the impact of the variability on the WLCC, performance and operational burden, 4) by demonstrating that PNs can be accelerated with modern computing techniques and explaining the process of conversion to

maximise acceleration with GPGPUs and finally, 5) with a new approach to Hybrid GAs which use a two stage optimisation approach using the fast, coarse surrogate model for the first phase and then a final honing using the full model.

- **A novel approach to comparing 2-Dimensional condition matrices was developed.** This used a network analysis approach with the novel feature that the distances between the nodes were set with the Mean Time to Failures (MTTFs). This new approach provides a framework for further 2-Dimensional comparisons that avoids the use of conversion factors/weightings which can be subjective.

- **Identification of variability in the system.** This was carried out by using literature, historical data and expert judgement. The various sources of variability in the industry practices were analysed and then the effect of variability was presented as a financial output. These results provide a new insight into the variability around the organisational practices of asset management of railway bridges.

- **PN model acceleration.** This was carried out with the use of GPGPUs. The process of converting a standard PN simulation algorithm to one specifically designed for GPGPUs was shown. Additionally, the factors which affect conversion were discussed as well as the results. This research should allow others to accelerate PN models with GPGPUs.

- **A new approach to Hybridising GAs.** This uses the fast surrogate model to rapidly find the area of interest and then switches over to the full model for the final honing of the individuals. This approach should have a wide appeal as it provided results 30x faster than the traditional method.

- **Identification of optimised policies.** These have been provided

with the use of the Hybrid-GA approach. The optimisation was carried out on the inspection policies as they should be easier to adopt by industry than changes to maintenance policies. The change in inspection policies should have both short and long-term benefits for railway bridge portfolio managers.

9.3 Future Developments

There are a number of key findings and novel approaches which have been developed for this research. A possible model addition could be a resource allocation module. The current organisational practice for maintaining railway bridges in the UK is with regional maintenance depots. However, each region encompasses a different amount of area and varying numbers of bridges. Additionally, each regional maintenance depot has a different amount of available resource e.g. equipment, plant and workforce. It is a complex task to quantify these resources, especially as they can change as equipment and plant become unavailable. This means that the model would have to take into account the region the bridge is located in and then allocate the resources accordingly. Since the resources are dynamically allocated bridge by bridge, there would have to be some consideration for other assets in the area requiring those same resources.

Another future development could be the inclusion of other sources of variability. For instance, incorporating variability in the delay times into the model. This would mean that the delay in scheduling the work would be variable and the time to complete the work would be variable. This would make the intervention process even more realistic. An interesting addition to this is that it would be possible to incorporate this into the probabilities of the imperfect repairs. The idea being that if an intervention took longer than normal, its possible that the resulting repair was of higher quality and therefore there is a higher chance of it being repaired to an A1

or B2 condition rather than a C3 condition. Additionally, if the repair took longer than normal, it is also possible that the cost of intervention was higher than normal as there were more resources required. This goes beyond introducing variability into one aspect of the model and begins to tie together variability in different processes. The interaction between these would have to be decided upon by significant amounts of data or expert judgement.

A possible final development could be the optimisation of a greater number of parameters. For instance, as well as minimising the WLCC and the probability of requiring replacement, a minimisation could be carried out including: 1) a minimisation of the cumulative number of possession hours, this would reduce the potential amount of penalties and fines the operator faces, 2) a minimisation of the total number of interventions which would be an effort to reduce the amount of site-visits that the operator would have to make which would have operational benefits including a possible reduction in the workforce required to maintain the portfolio of assets.

Appendix A

Model Code and Inputs

A.1 Petri-Net (PN) Model Inputs

The PN model developed uses a number of inputs to define the structure of the PN and the token characteristics within the PN. The following tables fully detail the inputs to the PN model.

Table A.1: Example input to construct the Places of the PN model.

Attribute	DataType	Example Entry	Description
"Place"	int	0	incremental place IDs
"Name"	string	"SubA1"	custom place name for ease of identification
"Coloured"	bool	1	ability to accept/generate coloured or non-coloured tokens to satisfy PN or Coloured Petri-Net (CPN) requirements

Table A.3: Example input to detail the tokens of the PN model.

Attribute	DataType	Example Entry	Description
"Token"	int	0	incremental token IDs

Table A.3: Example input to detail the tokens of the PN model.

Attribute	DataType	Example Entry	Description
“TokenType”	char	C	indicates whether token is coloured and contains tuples, or non-coloured
“IDstring”	string	“ONE1168”	used for custom identification
“AssetType”	string	BBU	used to identify the asset group
“CoastalProximityGroup”	int	1	relating to the Coastal Proximity ID’s found in the Local Environmental Factors (LEFs)
“GalvanicCorrosionGroup”	int	1	relating to the Galvanic Corrosion ID’s found in the LEFs
“ElementHierarchy”	int	4	used to indicate which bridge component the token represented e.g. 2 is Major Element
“ELR”	string	BGM	for identification of the Route on which the element resides
“Mileage”	double	23.5689	for identification of position of the component on the Route
“MajorElementCode”	string	DK	identification of the element using the industry standard format
“MajorElementNo”	int	3	identification of the element using the industry standard format
“MinorElementCode”	string	MGI	identification of the element using the industry standard format
“MinorElementNo”	int	3	identification of the element using the industry standard format

Table A.3: Example input to detail the tokens of the PN model.

Attribute	DataType	Example Entry	Description
"ElementID"	int	451895	identification of the element using the industry standard format
"ElementMaterial"	string	C	indicates the material of the element, e.g. C is concrete
"HistCondition"	int	3	Relates to the starting condition upon simulation, insertion to the relevant Place ID
"Territory"	string	"Scotland"	determines the principality in which the element resides
"Geology"	string	"Sandy Loam"	used to determine the geology beneath the asset
"Altitude"	int	128	Relates to the meters above sea level of the element which the token represents
"ConditionOutput"	bool	1	used to determine if detailed outputs are required after simulation has finished

A.2 Petri-Net (PN) Model Code

The C++ code, in which the model was implemented, has been uploaded to the University of Nottingham eThesis electronic archive in accordance with the university guidelines on supplementary material.

Table A.2: Example input to construct the Transitions of the PN model.

Attribute	DataType	Example Entry	Description
"Transition"	int	0	incremental transition IDs
"Name"	string	"MinorG4"	custom transition name for ease of identification
"DelayType"	int	1	type of transition delay e.g. 1 is fixed delay type, 3 is a Weibull based delay type
"DelayParameters"	vec(int)	1	the calibrated parameter corresponding to "DelayType"
"DecisionFunctions"	vec(int)	2	transition output decision function (e.g. 2 is probabilistically defined for each output place)
"Probabilities"	vec(double)	0.5,0.5	the calibrated parameters corresponding to "Decision-Functions"
"ResetPlaces"	vec(int)	2,3	if the transition has been given the ability to reset (i.e. delete) tokens in particular places upon firing, relevant place IDs are detailed here
"DelayPlaces"	vec(int)	2,3	if conditional firing delay is used, the relevant placeIDs are detailed here
"InputPlaces"	vec(int)	1	placeID(s) to enable transition
"DashedInputPlaces"	vec(int)	1	relevant place IDs are detailed here which relate to the functions enabled in "DecisionFunctions"
"OutputPlaces"	vec(int)	1	placeID(s) to generate tokens upon firing
"DashedOutputPlaces"	vec(int)	1	relevant place IDs are detailed here which relate to the functions enabled in "DecisionFunctions"

Appendix B

Data Sources

B.1 Example Data Sources

The data provided for this research is not able to be distributed for confidentiality reasons. However, the following tables give fictitious representations of the data which are in the same format as the data provided for this research.

Table B.1: Fictitious representation of the element inspection data.

ElementID	ELR	Mileage	Major Element Code	Major Element No	Minor Element Code	Minor Element No	Structure Type	Material	ExamDate	SevEx
A0001	PQR	18.23	ES	3	ABT	1	BBU	C	01/06/1997	B2
A0002	PQR	18.23	ES	3	ABT	1	BBU	C	01/06/1999	B2
A0003	PQR	18.23	ES	3	ABT	1	BBU	C	01/06/2001	B4
A0004	PQR	18.23	ES	3	ABT	1	BBU	C	01/06/2003	B4
A0005	PQR	18.23	ES	3	ABT	1	BBU	C	01/06/2005	B4
A0006	PQR	18.23	ES	3	ABT	1	BBU	C	01/06/2007	B5
A0007	PQR	18.23	ES	3	ABT	1	BBU	C	01/06/2009	B5
A0008	PQR	18.23	ES	3	ABT	1	BBU	C	01/06/2011	B6
A0009	PQR	18.23	ES	3	ABT	1	BBU	C	01/06/2013	A1
A0010	PQR	18.23	ES	3	ABT	1	BBU	C	01/06/2015	B2
B1023	TFC	102.8	DCK	1	DCK	14	BBO	B	01/02/1998	C3
B1024	TFC	102.8	DCK	1	DCK	14	BBO	B	01/02/2000	C3
B1025	TFC	102.8	DCK	1	DCK	14	BBO	B	01/02/2002	C4
B1026	TFC	102.8	DCK	1	DCK	14	BBO	B	01/02/2004	C4
B1027	TFC	102.8	DCK	1	DCK	14	BBO	B	01/02/2006	C4
B1028	TFC	102.8	DCK	1	DCK	14	BBO	B	01/02/2008	C5
B1029	TFC	102.8	DCK	1	DCK	14	BBO	B	01/02/2010	C5
B1029	TFC	102.8	DCK	1	DCK	14	BBO	B	01/02/2010	C5
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table B.2: Fictitious representation of the element maintenance data.

StructureID	ELR	Mileage	MonitorID	Area	Date Issued	Response Time	Brief Scope Of Works	Work Location On structure	...
A1423	ECI	15.63	001A	Lancs and Cumbria	01/02/2000	6 weeks	Brick Rebuild	Wing Wall	...
B1892	NEO	48.12	002A	Scotland	01/04/2000	3 weeks	Concrete Repair	Parapet	...
C2859	OFV	2.13	003A	Wales	01/07/2000	12 weeks	Concrete Repair	Girder	...
D7492	FSC	10.59	004A	Yorkshire	01/07/2000	9 months	Girder Replacement	Girder	...
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

...	Work Quantification	Work Defect	Date Started	Date Complete	Paid To Date	Percentage Complete
...	2.0m2	Loss of MUs	01/03/2000	01/04/2000	100mu	100
...	0.5m2	Loss of section	01/05/2000	01/06/2000	50mu	60
...	3.5m2	Loss of section	01/08/2000	01/09/2000	200mu	95
...	1unit	Corroded section	01/09/2000	01/10/2000	750mu	100
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Appendix C

Analysis Results

C.1 Detailed Local Environmental Factor (LEF) Outputs

Table C.1: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to <39 frost days per year.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	15174	635	992	1691	2849	19868	1840	2863	4533	4374	20212	4081	5664	7173	10926	21850	4850	6133	9265	9958	Inf	11318	6702	7241	8037	Inf	15299	15371	9032	9585
B2	Inf	0	314	671	1370	2529	4694	449	2542	4212	4054	5038	2690	4273	5782	9643	6676	3459	4741	7873	8566	Inf	7226	5311	5849	6645	Inf	11207	11279	7640	8193
B3	Inf	Inf	0	357	1056	2215	Inf	1206	2228	3898	3740	Inf	3447	5029	6538	10292	Inf	4216	5498	8630	9323	Inf	10683	6067	6606	7402	Inf	14665	14737	8397	8950
B4	Inf	Inf	Inf	0	699	1858	Inf	Inf	1871	3541	3383	Inf	Inf	5629	7138	9935	Inf	Inf	11665	10156	10849	Inf	Inf	12234	12773	13569	Inf	Inf	Inf	14564	15117
B5	Inf	Inf	Inf	Inf	0	1159	Inf	Inf	Inf	4005	2684	Inf	Inf	Inf	Inf	9236	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1525	Inf	Inf	Inf	Inf	8077	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	495	2591	4261	9903	344	642	2224	3733	7594	1982	1411	2693	5825	6518	Inf	2531	3263	3801	4597	Inf	6513	6585	5592	6145
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2095	3765	9408	Inf	2241	3824	5333	9194	Inf	3010	4292	7424	8117	Inf	9477	4862	5400	6196	Inf	13459	13531	7191	7744
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1670	7312	Inf	Inf	3758	5267	9128	Inf	Inf	9794	8285	8978	Inf	Inf	10363	10902	11698	Inf	Inf	Inf	12693	13246
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	5642	Inf	Inf	Inf	Inf	12194	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	6552	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	298	1880	3389	7250	1638	1067	2349	5481	6174	Inf	2187	2919	3457	4253	Inf	6169	6241	5248	5801
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1583	3092	6953	Inf	769	2051	5183	5876	Inf	7236	2621	3159	3955	Inf	11218	11290	4950	5503
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1509	5370	Inf	Inf	6036	4527	5220	Inf	Inf	6605	7144	7940	Inf	Inf	Inf	8935	9488
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	3861	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	303	1585	4717	5410	Inf	549	2154	2693	3489	Inf	4531	4603	4484	5037
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1282	4414	5107	Inf	6467	1852	2390	3186	Inf	10449	10521	4181	4734
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	3132	3825	Inf	Inf	569	1108	1904	Inf	Inf	Inf	2899	3452
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	693	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	474	2205	2744	3540	Inf	4456	4528	4535	5088
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1731	2270	3066	Inf	3982	4054	4061	4614
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	539	1335	Inf	Inf	Inf	2330	2883
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	796	Inf	Inf	Inf	1791	2344
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1548
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	72	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.2: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to 39-48 frost days per year.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	2656	354	1081	1546	2035	12201	1143	1760	2439	4826	17853	2436	3352	3990	6142	Inf	3425	4097	4781	5066	Inf	4093	5108	5368	5458	Inf	13165	58525	17212	18580
B2	Inf	0	522	1248	1714	2203	9545	1183	1799	2478	4865	15197	2476	3391	4030	6182	Inf	3464	4136	4821	5106	Inf	4132	5147	5407	5498	Inf	13204	58564	17251	18619
B3	Inf	Inf	0	726	1192	1681	Inf	789	1406	2085	4471	Inf	2082	2997	3636	5788	Inf	3070	3742	4427	4712	Inf	3738	4754	5014	5104	Inf	12810	58170	16858	18226
B4	Inf	Inf	Inf	0	465	955	Inf	Inf	4631	5310	4348	Inf	Inf	6233	6872	6061	Inf	Inf	6978	7663	7948	Inf	Inf	7989	8249	8340	Inf	Inf	Inf	20093	21461
B5	Inf	Inf	Inf	Inf	0	489	Inf	Inf	Inf	7692	3882	Inf	Inf	Inf	13550	5596	Inf	Inf	Inf	16778	9304	Inf	Inf	Inf	18809	9907	Inf	Inf	Inf	30653	32021
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	3393	Inf	Inf	Inf	Inf	5107	Inf	Inf	Inf	Inf	8815	Inf	Inf	Inf	Inf	9417	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	514	1131	1810	4196	5652	1807	2722	3361	5513	Inf	2795	3467	4152	4437	Inf	3463	4479	4739	4829	Inf	12535	57895	16583	17951
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	617	1296	3682	Inf	1293	2208	2847	4999	Inf	2281	2953	3638	3923	Inf	2950	3965	4225	4315	Inf	12022	57382	16069	17437
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	679	3066	Inf	Inf	1602	2241	4393	Inf	Inf	2347	3032	3317	Inf	Inf	3358	3619	3709	Inf	Inf	Inf	15463	16831
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2387	Inf	Inf	Inf	5858	4100	Inf	Inf	Inf	9086	6934	Inf	Inf	Inf	11117	7537	Inf	Inf	Inf	22961	24329
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1714	Inf	Inf	Inf	Inf	5422	Inf	Inf	Inf	Inf	6024	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	236	1151	1790	3942	Inf	648	1896	2581	2866	Inf	1316	2712	3115	3258	Inf	10388	55748	14959	16327
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	915	1554	3706	Inf	988	1660	2345	2630	Inf	1656	2672	2932	3022	Inf	10728	56088	14776	16144
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	639	2791	Inf	Inf	745	1430	1715	Inf	Inf	1756	2017	2107	Inf	Inf	Inf	13861	15229
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2152	Inf	Inf	Inf	3228	1076	Inf	Inf	Inf	5259	1679	Inf	Inf	Inf	17103	18471
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	3708	Inf	Inf	Inf	Inf	4311	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	336	1682	2366	3611	Inf	1004	2400	2803	3042	Inf	10076	55436	14647	16015
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1346	2030	3275	Inf	668	2064	2467	2706	Inf	9740	55100	14311	15679
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	685	1929	Inf	Inf	1011	1271	1362	Inf	Inf	Inf	13115	14483
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1245	Inf	Inf	Inf	2031	677	Inf	Inf	Inf	13875	15243
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	603	Inf	Inf	Inf	Inf	Inf
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	169	1565	1968	2207	1296	2592	54601	13812	15180
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1396	1799	2038	Inf	9072	54432	13643	15011
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	403	642	Inf	Inf	Inf	12247	13615
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	239	Inf	Inf	Inf	11844	13212
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1296	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1368
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.3: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to >48 frost days per year.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	1428	377	1563	2161	2810	12393	1682	2938	3919	5886	Inf	2601	3475	4589	7005	Inf	3292	4321	5368	7480	Inf	4502	5039	5300	5840	Inf	44390	45422	Inf	31220
B2	Inf	0	682	1868	2466	3115	10965	1566	2823	3803	6191	Inf	2486	3360	4473	6889	Inf	3176	4205	5252	7364	Inf	4386	4923	5184	5725	Inf	44274	45306	Inf	31105
B3	Inf	Inf	0	1186	1784	2433	Inf	1305	2561	3541	5509	Inf	2224	3098	4212	6628	Inf	2914	3943	4990	7102	Inf	4125	4662	4922	5463	Inf	44013	45045	Inf	30843
B4	Inf	Inf	Inf	0	599	1247	Inf	Inf	2790	3771	4323	Inf	Inf	5473	6587	7916	Inf	Inf	8019	7931	9081	Inf	Inf	8738	8987	8787	Inf	Inf	Inf	Inf	34167
B5	Inf	Inf	Inf	Inf	0	649	Inf	Inf	Inf	6339	3725	Inf	Inf	Inf	15043	10484	Inf	Inf	Inf	18667	11648	Inf	Inf	Inf	19723	19524	Inf	Inf	Inf	Inf	44904
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	3346	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	515	1772	2752	5754	Inf	1435	2309	3423	5839	Inf	2125	3154	4201	6313	Inf	3336	3873	4133	4674	Inf	43224	44256	Inf	30054
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1256	2237	5238	Inf	919	1793	2907	5323	Inf	1610	2639	3686	5798	Inf	2820	3357	3618	4158	Inf	42708	43740	Inf	29538
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	980	3982	Inf	Inf	2683	3797	5125	Inf	Inf	5229	5141	6290	Inf	Inf	5947	6197	5997	Inf	Inf	Inf	Inf	31377
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	3002	Inf	Inf	Inf	8705	4145	Inf	Inf	Inf	12329	5310	Inf	Inf	Inf	13385	13185	Inf	Inf	Inf	Inf	38565
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	171	1045	2158	4574	Inf	861	1890	2937	5049	Inf	2071	2608	2869	3410	Inf	41959	42991	Inf	28790
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	874	1988	4404	Inf	690	1719	2766	4878	Inf	1901	2438	2698	3239	Inf	41789	42821	Inf	28619
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1114	3530	Inf	Inf	2546	2458	4570	Inf	Inf	3264	3514	3314	Inf	Inf	Inf	Inf	28694
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2416	Inf	Inf	Inf	3624	3581	Inf	Inf	Inf	4680	4480	Inf	Inf	Inf	Inf	29860
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1165	Inf	Inf	Inf	Inf	13045	Inf	Inf	Inf	Inf	38425
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	600	1629	2676	4788	Inf	450	1203	1463	2004	Inf	40338	41370	Inf	27384
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1029	2076	4188	Inf	1211	1748	2008	2549	Inf	41099	42131	Inf	27929
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1047	3159	Inf	Inf	719	979	1520	Inf	Inf	Inf	Inf	26900
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2112	Inf	Inf	Inf	1056	856	Inf	Inf	Inf	Inf	26236
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	11880	Inf	Inf	Inf	Inf	37260
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	283	1035	1296	1837	Inf	40171	41203	Inf	27217
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	753	1013	1554	Inf	39888	40920	Inf	26934
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	260	801	Inf	Inf	Inf	Inf	26181
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	541	Inf	Inf	Inf	Inf	25921
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	25380
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1032	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	456
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.4: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to Galvanic Corrosion Rank 2/3.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	4100	909	1698	2267	3389	24599	2425	3502	4079	5057	Inf	3524	4609	6947	8140	Inf	4646	5402	6546	7657	Inf	7219	5958	6689	7179	Inf	Inf	57907	Inf	7026
B2	Inf	0	844	1633	2202	3324	45972	582	1659	2236	3214	Inf	1681	2766	5104	6297	Inf	2803	3559	4703	5814	Inf	5376	4115	4846	5336	Inf	Inf	56064	Inf	5183
B3	Inf	Inf	0	789	1358	2481	Inf	1516	2593	3170	4148	Inf	2615	3700	6038	7231	Inf	3737	4493	5637	6748	Inf	6310	5049	5780	6270	Inf	Inf	56998	Inf	6117
B4	Inf	Inf	Inf	0	569	1691	Inf	Inf	11077	11654	4931	Inf	Inf	12621	14959	16152	Inf	Inf	13414	14558	15669	Inf	Inf	13969	14701	15190	Inf	Inf	Inf	Inf	15037
B5	Inf	Inf	Inf	Inf	0	1122	Inf	Inf	Inf	45008	4362	Inf	Inf	Inf	55520	16458	Inf	Inf	Inf	56912	58024	Inf	Inf	Inf	58690	57900	Inf	Inf	Inf	Inf	59027
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	3240	Inf	Inf	Inf	Inf	15336	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	215	1292	1869	2847	Inf	1314	2399	4737	5930	Inf	2436	3192	4335	5447	Inf	5008	3747	4479	4968	Inf	Inf	55696	Inf	4815
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1077	1654	2632	Inf	1099	2184	4522	5715	Inf	2222	2977	4121	5232	Inf	4794	3533	4264	4754	Inf	Inf	55482	Inf	4601
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	577	1555	Inf	Inf	1544	3882	5075	Inf	Inf	2337	3481	4592	Inf	Inf	2893	3624	4113	Inf	Inf	Inf	Inf	3961
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	978	Inf	Inf	Inf	10512	5256	Inf	Inf	Inf	11904	13016	Inf	Inf	Inf	13682	12892	Inf	Inf	Inf	Inf	14019
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	12096	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	161	1246	3584	4777	Inf	756	2039	3182	4294	Inf	3328	2594	3326	3815	Inf	Inf	54016	Inf	3662
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1085	3423	4616	Inf	1122	1878	3022	4133	Inf	3695	2434	3165	3654	Inf	Inf	54383	Inf	3502
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2338	3531	Inf	Inf	793	1937	3048	Inf	Inf	1349	2080	2570	Inf	Inf	Inf	Inf	2417
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1193	Inf	Inf	Inf	1392	2504	Inf	Inf	Inf	3170	2380	Inf	Inf	Inf	Inf	3507
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1206	4743	5887	6998	Inf	179	1763	2494	2984	Inf	Inf	50867	Inf	2831
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	3537	4681	5792	Inf	2572	4092	4824	5313	Inf	Inf	53260	Inf	5160
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1144	2255	Inf	Inf	555	1287	1776	Inf	Inf	Inf	Inf	1623
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1112	Inf	Inf	Inf	1778	988	Inf	Inf	Inf	Inf	2115
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1308	Inf	Inf	Inf	Inf	Inf
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	98	1682	2414	2903	1152	Inf	50786	Inf	2750
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1584	2316	2805	Inf	Inf	50688	Inf	2652
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	732	1221	Inf	Inf	Inf	Inf	1068
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	489	Inf	Inf	Inf	Inf	336
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	576
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.5: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to Galvanic Corrosion Rank 4.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	2879	202	2231	3157	3462	12431	1691	3009	3936	5539	Inf	2666	3823	5105	8408	Inf	3330	5745	6085	7041	Inf	3507	4371	4574	4720	Inf	10707	11211	Inf	8599
B2	Inf	0	320	2350	3275	3580	9552	637	1955	2881	4485	Inf	1612	2769	4050	7353	Inf	2275	4691	5030	5986	Inf	2453	3317	3519	3665	Inf	9653	10157	Inf	7544
B3	Inf	Inf	0	2030	2955	3260	Inf	1490	2807	3734	5337	Inf	2465	3621	4903	8206	Inf	3128	5544	5883	6839	Inf	3305	4169	4372	4518	Inf	10505	11009	Inf	8397
B4	Inf	Inf	Inf	0	926	1231	Inf	Inf	1375	2301	3905	Inf	Inf	3434	4715	8018	Inf	Inf	5356	5695	6651	Inf	Inf	7261	7451	6061	Inf	Inf	Inf	Inf	9940
B5	Inf	Inf	Inf	Inf	0	305	Inf	Inf	Inf	3993	3872	Inf	Inf	Inf	14415	9722	Inf	Inf	Inf	17718	17718	Inf	Inf	Inf	20586	18084	Inf	Inf	Inf	Inf	21963
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	4464	Inf	Inf	Inf	Inf	10314	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	234	1552	2478	4082	Inf	1209	2366	3647	6950	Inf	1872	4288	4627	5583	Inf	2050	2914	3116	3262	Inf	9250	9754	Inf	7141
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1318	2244	3848	Inf	975	2132	3413	6716	Inf	1638	4054	4393	5349	Inf	1816	2680	2882	3028	Inf	9016	9520	Inf	6907
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	926	2530	Inf	Inf	2059	3340	6643	Inf	Inf	3981	4320	5276	Inf	Inf	5886	6076	4686	Inf	Inf	Inf	Inf	8565
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1603	Inf	Inf	Inf	10422	7453	Inf	Inf	Inf	13725	13725	Inf	Inf	Inf	16593	14091	Inf	Inf	Inf	Inf	17970
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	5850	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	201	1358	2639	5942	Inf	345	3280	3619	4575	Inf	522	1386	1588	1734	Inf	7722	8226	Inf	5613
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1157	2438	5741	Inf	663	3079	3418	4374	Inf	841	1705	1907	2053	Inf	8041	8545	Inf	5932
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1282	4585	Inf	Inf	1922	2262	3218	Inf	Inf	3827	4018	2628	Inf	Inf	Inf	Inf	6507
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	3303	Inf	Inf	Inf	3303	3303	Inf	Inf	Inf	6171	3669	Inf	Inf	Inf	Inf	7548
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	141	3756	4432	5388	Inf	318	1182	1385	1531	Inf	7518	8022	Inf	5410
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	3615	4291	5247	Inf	177	1041	1244	1390	Inf	7377	7881	Inf	5269
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	676	1632	Inf	Inf	1905	2095	1042	Inf	Inf	Inf	Inf	4921
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	956	Inf	Inf	Inf	2868	366	Inf	Inf	Inf	Inf	4245
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1128	Inf	Inf	Inf	Inf	5007
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	192	1056	1258	1405	Inf	7392	7896	Inf	5284
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	864	1066	1213	Inf	7200	7704	Inf	5092
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	202	349	Inf	Inf	Inf	Inf	4228
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	146	Inf	Inf	Inf	Inf	4025
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	3879
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	504	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	288
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.6: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to Galvanic Corrosion Rank 5.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	12324	148	713	1600	3004	2241	914	1065	2013	2781	Inf	1780	2372	Inf	Inf	Inf	3508	Inf	2840	Inf	Inf	3671	4175	3200	Inf	Inf	Inf	Inf	Inf	Inf
B2	Inf	0	272	837	1724	3128	Inf	1038	1189	2137	2905	Inf	1903	2496	Inf	Inf	Inf	3631	Inf	2964	Inf	Inf	3795	4299	3324	Inf	Inf	Inf	Inf	Inf	Inf
B3	Inf	Inf	0	565	1452	2856	Inf	766	917	1865	2633	Inf	1631	2224	Inf	Inf	Inf	3359	Inf	2692	Inf	Inf	3523	4027	3052	Inf	Inf	Inf	Inf	Inf	Inf
B4	Inf	Inf	Inf	0	887	2291	Inf	Inf	3546	4494	5262	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
B5	Inf	Inf	Inf	Inf	0	1404	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	108	259	1207	1975	Inf	974	1566	Inf	Inf	Inf	2702	Inf	2034	Inf	Inf	2865	3369	2394	Inf	Inf	Inf	Inf	Inf	Inf
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	151	1099	1867	Inf	866	1458	Inf	Inf	Inf	2594	Inf	1926	Inf	Inf	2757	3261	2286	Inf	Inf	Inf	Inf	Inf	Inf
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	948	1716	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	768	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	592	Inf	Inf	Inf	1728	Inf	1060	Inf	Inf	1891	2395	1420	Inf	Inf	Inf	Inf	Inf	Inf
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	468	Inf	Inf	Inf	Inf	828	Inf	Inf	Inf	Inf	Inf	Inf
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	126	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	180	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	72	Inf	Inf	Inf	Inf	235	739	843	Inf	Inf	Inf	Inf	Inf	Inf
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	163	667	771	Inf	Inf	Inf	Inf	Inf	Inf
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	288	Inf	Inf	Inf	144	248	Inf	Inf	Inf	Inf	Inf	Inf
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	360	Inf	Inf	Inf	Inf	Inf	Inf
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	504	608	Inf	Inf	Inf	Inf	Inf	Inf
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	104	Inf	Inf	Inf	Inf	Inf	Inf
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.7: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to Rainfall <635mm.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	3325	525	885	1391	3031	6965	1864	1831	3826	2801	Inf	3931	5407	6940	11236	Inf	4785	7079	7860	10830	Inf	9349	8453	8711	8181	Inf	55789	Inf	11024	11979
B2	Inf	0	241	601	1106	2747	3640	1174	1546	3542	2517	Inf	3241	4717	6250	10546	Inf	4095	6389	7170	10140	Inf	8659	7763	8021	7491	Inf	55099	Inf	10334	11289
B3	Inf	Inf	0	360	865	2505	Inf	1339	1305	3301	2276	Inf	3406	4882	6415	10711	Inf	4260	6554	7335	10305	Inf	8824	7927	8185	7656	Inf	55264	Inf	10498	11454
B4	Inf	Inf	Inf	0	505	2145	Inf	Inf	945	2940	1916	Inf	Inf	6738	8271	12567	Inf	Inf	8410	9191	12161	Inf	Inf	9783	10041	9512	Inf	Inf	Inf	12354	13310
B5	Inf	Inf	Inf	Inf	0	1640	Inf	Inf	Inf	3617	1410	Inf	Inf	Inf	Inf	20886	Inf	Inf	Inf	Inf	29022	Inf	Inf	Inf	Inf	29714	Inf	Inf	Inf	Inf	33512
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	2295	Inf	Inf	Inf	Inf	21771	Inf	Inf	Inf	Inf	29907	Inf	Inf	Inf	Inf	30599	Inf	Inf	Inf	Inf	34397
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	532	2544	4539	18831	Inf	2599	4075	5608	9904	Inf	3453	5747	6528	9498	Inf	8017	7120	7379	6849	Inf	54457	Inf	9692	10647
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2012	4007	18299	Inf	2067	3543	5076	9372	Inf	2921	5215	5996	8966	Inf	7485	6588	6847	6317	Inf	53925	Inf	9160	10115
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1995	16287	Inf	Inf	5793	7326	11622	Inf	Inf	7465	8245	11215	Inf	Inf	8838	9096	8566	Inf	Inf	Inf	11409	12364
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	14292	Inf	Inf	Inf	Inf	33768	Inf	Inf	Inf	Inf	41904	Inf	Inf	Inf	Inf	42595	Inf	Inf	Inf	Inf	46393
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	19476	Inf	Inf	Inf	Inf	27612	Inf	Inf	Inf	Inf	28303	Inf	Inf	Inf	Inf	32101
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	213	1689	3222	7518	Inf	498	3361	4142	7112	Inf	5062	4735	4993	4463	Inf	51502	Inf	7306	8261
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1476	3009	7305	Inf	854	3148	3928	6898	Inf	5418	4521	4779	4250	Inf	51858	Inf	7092	8048
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1533	5829	Inf	Inf	1672	2453	5423	Inf	Inf	3046	3304	2774	Inf	Inf	Inf	5617	6572
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	4296	Inf	Inf	Inf	3222	6192	Inf	Inf	Inf	4707	3543	Inf	Inf	Inf	7020	7341
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	8136	Inf	Inf	Inf	Inf	8827	Inf	Inf	Inf	Inf	12625
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	182	5624	7760	10730	Inf	1548	3483	3741	3951	Inf	47988	Inf	6054	7749
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	5442	7578	10548	Inf	4564	5442	5700	5910	Inf	51004	Inf	8013	9708
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2136	5106	Inf	Inf	1373	1631	1842	Inf	Inf	Inf	3944	5640
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2970	Inf	Inf	Inf	1485	321	Inf	Inf	Inf	3798	4119
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	691	Inf	Inf	Inf	Inf	4489
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	342	2277	2535	2745	Inf	46782	Inf	4848	6543
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1935	2193	2403	Inf	46440	Inf	4506	6201
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	258	468	Inf	Inf	Inf	2571	4266
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	210	Inf	Inf	Inf	2313	4008
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	3798
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.8: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to Rainfall 635mm-775mm.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	2486	398	1291	1668	2128	14218	1352	2002	3100	5259	14845	2258	3000	3729	6211	17203	3131	3727	4593	5475	Inf	3903	4422	4730	5092	Inf	10593	12285	Inf	Inf
B2	Inf	0	696	1589	1966	2426	13527	757	1407	2505	5557	14153	1662	2404	3134	5616	16511	2536	3132	3997	4879	Inf	3307	3827	4134	4497	Inf	9998	11690	Inf	Inf
B3	Inf	Inf	0	893	1270	1730	Inf	954	1604	2702	4861	Inf	1860	2602	3331	5813	Inf	2733	3329	4194	5076	Inf	3505	4024	4332	4694	Inf	10195	11887	Inf	Inf
B4	Inf	Inf	Inf	0	377	837	Inf	Inf	6345	5066	3968	Inf	Inf	7775	8504	8177	Inf	Inf	10953	10556	9045	Inf	Inf	11648	11955	11966	Inf	Inf	Inf	Inf	Inf
B5	Inf	Inf	Inf	Inf	0	460	Inf	Inf	Inf	4688	3591	Inf	Inf	Inf	11256	7800	Inf	Inf	Inf	16116	8668	Inf	Inf	Inf	17669	11589	Inf	Inf	Inf	Inf	Inf
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	3131	Inf	Inf	Inf	Inf	14183	Inf	Inf	Inf	Inf	15052	Inf	Inf	Inf	Inf	17973	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	569	1220	2317	9706	626	846	1588	2317	5429	2984	1719	2315	3180	4062	Inf	2491	3010	3318	3680	Inf	9181	10873	Inf	Inf
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	650	1748	9137	Inf	906	1648	2377	4859	Inf	1779	2375	3240	4122	Inf	2551	3070	3378	3740	Inf	9241	10933	Inf	Inf
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1098	8487	Inf	Inf	1429	2159	4209	Inf	Inf	4607	4210	3981	Inf	Inf	5303	5610	5762	Inf	Inf	Inf	Inf	Inf
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	7389	Inf	Inf	Inf	6568	3111	Inf	Inf	Inf	11428	3980	Inf	Inf	Inf	12980	6901	Inf	Inf	Inf	Inf	Inf
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	11052	Inf	Inf	Inf	Inf	11921	Inf	Inf	Inf	Inf	14842	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	219	961	1691	8981	2358	1093	1689	2554	3436	Inf	1864	2384	2691	3054	Inf	8555	10247	Inf	Inf
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	742	1471	8761	Inf	873	1469	2335	3217	Inf	1645	2164	2472	2835	Inf	8335	10027	Inf	Inf
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	729	8019	Inf	Inf	3178	2781	2552	Inf	Inf	3873	4181	4333	Inf	Inf	Inf	Inf	Inf
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	7290	Inf	Inf	Inf	4860	1823	Inf	Inf	Inf	6412	4744	Inf	Inf	Inf	Inf	Inf
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	869	Inf	Inf	Inf	Inf	3790	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	643	1239	2104	2986	Inf	598	1622	1929	2292	Inf	7289	8981	Inf	Inf
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	596	1461	2343	Inf	772	1291	1599	1961	Inf	7462	9154	Inf	Inf
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	865	1747	Inf	Inf	695	1003	1365	Inf	Inf	Inf	Inf	Inf
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	882	Inf	Inf	Inf	1552	1552	Inf	Inf	Inf	Inf	Inf
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	2921	Inf	Inf	Inf	Inf	Inf
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	299	1322	1630	1993	1596	2388	4080	Inf	Inf
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1023	1331	1693	Inf	6690	8382	Inf	Inf
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	307	670	Inf	Inf	Inf	Inf	Inf
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	363	Inf	Inf	Inf	Inf	Inf
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	792	2484	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1692	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1080
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.9: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to Rainfall >775mm.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	2657	419	1363	2201	2987	10055	1416	2519	3153	4278	Inf	2760	3997	5002	5841	Inf	3433	4799	5546	9518	Inf	4716	5475	5869	6290	Inf	13853	14213	17191	17755
B2	Inf	0	558	1503	2340	3127	7398	1233	2336	2970	4095	Inf	2577	3814	4818	5658	Inf	3250	4615	5362	9334	Inf	4533	5292	5686	6107	Inf	13670	14030	17008	17572
B3	Inf	Inf	0	944	1782	2568	Inf	997	2100	2734	3860	Inf	2341	3578	4583	5422	Inf	3015	4380	5127	9099	Inf	4298	5056	5451	5872	Inf	13434	13794	16773	17337
B4	Inf	Inf	Inf	0	838	1624	Inf	Inf	4219	4853	4602	Inf	Inf	6180	7185	6164	Inf	Inf	7376	8123	12095	Inf	Inf	8052	8447	8868	Inf	Inf	Inf	19769	20333
B5	Inf	Inf	Inf	Inf	0	786	Inf	Inf	Inf	12780	3764	Inf	Inf	Inf	19534	5326	Inf	Inf	Inf	38290	15046	Inf	Inf	Inf	40276	15438	Inf	Inf	Inf	51598	52162
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	2978	Inf	Inf	Inf	Inf	4540	Inf	Inf	Inf	Inf	14260	Inf	Inf	Inf	Inf	14651	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	461	1564	2198	3324	Inf	1805	3042	4047	4886	Inf	2479	3844	4591	8563	Inf	3762	4520	4915	5336	Inf	12898	13258	16237	16801
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1103	1737	2862	Inf	1344	2581	3585	4425	Inf	2017	3382	4129	8101	Inf	3300	4059	4453	4874	Inf	12437	12797	15775	16339
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	634	1759	Inf	Inf	1961	2966	3322	Inf	Inf	3156	3903	7875	Inf	Inf	3833	4227	4648	Inf	Inf	Inf	15549	16113
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1126	Inf	Inf	Inf	6754	2688	Inf	Inf	Inf	25510	12408	Inf	Inf	Inf	27496	12800	Inf	Inf	Inf	38818	39382
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1562	Inf	Inf	Inf	Inf	11282	Inf	Inf	Inf	Inf	11674	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	278	1515	2520	4151	Inf	952	2317	3064	7036	Inf	2235	2993	3388	3808	Inf	11371	11731	14710	15274
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1237	2242	3873	Inf	673	2039	2786	6758	Inf	1956	2715	3109	3530	Inf	11093	11453	14431	14995
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1005	2636	Inf	Inf	1195	1942	5914	Inf	Inf	1872	2266	2687	Inf	Inf	Inf	13588	14152
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1631	Inf	Inf	Inf	18756	11351	Inf	Inf	Inf	20742	11742	Inf	Inf	Inf	32064	32628
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	9720	Inf	Inf	Inf	Inf	10112	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	140	1505	2252	6224	Inf	1422	2181	2576	2996	Inf	10559	10919	13898	14462
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1365	2112	6084	Inf	1283	2042	2436	2857	Inf	10420	10780	13758	14322
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	747	4719	Inf	Inf	677	1071	1492	Inf	Inf	Inf	12393	12957
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	3972	Inf	Inf	Inf	1986	745	Inf	Inf	Inf	13308	13872
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	392	Inf	Inf	Inf	Inf	Inf
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	160	1132	1526	2029	Inf	9297	9657	12848	13412
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	972	1366	1870	Inf	9137	9497	12688	13252
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	394	898	Inf	Inf	Inf	11716	12280
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	503	Inf	Inf	Inf	11322	11886
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	360	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	564
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.10: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to mean maximum temperatures <19c.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	2648	380	1385	2151	2998	8660	1393	2326	3088	4577	Inf	2680	4050	5026	6151	Inf	3753	4985	5947	8323	Inf	5011	5975	6387	6861	Inf	14069	14537	17799	10185
B2	Inf	0	396	1401	2167	3014	6012	1409	2342	3104	4593	Inf	2696	4066	5042	6167	Inf	3769	5001	5963	8339	Inf	5027	5990	6403	6877	Inf	14085	14553	17815	10201
B3	Inf	Inf	0	1004	1770	2618	Inf	1013	1946	2708	4197	Inf	2299	3669	4646	5770	Inf	3373	4604	5566	7942	Inf	4631	5594	6007	6480	Inf	13688	14156	17419	9804
B4	Inf	Inf	Inf	0	766	1613	Inf	Inf	3032	3794	5283	Inf	Inf	4785	5762	6886	Inf	Inf	9831	10634	9416	Inf	Inf	11068	11481	9992	Inf	Inf	Inf	22893	13316
B5	Inf	Inf	Inf	Inf	0	847	Inf	Inf	Inf	11426	9155	Inf	Inf	Inf	16810	14465	Inf	Inf	Inf	21682	20464	Inf	Inf	Inf	23379	21040	Inf	Inf	Inf	34791	24364
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	8308	Inf	Inf	Inf	Inf	13618	Inf	Inf	Inf	Inf	24598	Inf	Inf	Inf	Inf	25174	Inf	Inf	Inf	Inf	28498
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	549	1482	2244	3733	Inf	1835	3205	4182	5306	Inf	2909	4140	5102	7478	Inf	4166	5130	5543	6016	Inf	13224	13692	16955	9340
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	933	1695	3184	Inf	1287	2657	3633	4758	Inf	2360	3592	4554	6930	Inf	3618	4581	4994	5467	Inf	12675	13143	16406	8791
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	762	2251	Inf	Inf	1753	2730	3854	Inf	Inf	6799	7602	6384	Inf	Inf	8036	8449	6960	Inf	Inf	Inf	19861	10284
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1489	Inf	Inf	Inf	5383	6508	Inf	Inf	Inf	10255	9037	Inf	Inf	Inf	11953	9613	Inf	Inf	Inf	23365	12937
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	5310	Inf	Inf	Inf	Inf	16290	Inf	Inf	Inf	Inf	16866	Inf	Inf	Inf	Inf	20190
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	318	1688	2665	3789	Inf	1391	2623	3585	5961	Inf	2649	3613	4025	4499	Inf	11707	12175	15437	7823
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1370	2347	3471	Inf	1073	2305	3267	5643	Inf	2331	3295	3707	4181	Inf	11389	11857	15119	7505
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	977	2101	Inf	Inf	5046	5849	4631	Inf	Inf	6283	6696	5207	Inf	Inf	Inf	18108	8531
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1124	Inf	Inf	Inf	4872	3654	Inf	Inf	Inf	6569	4230	Inf	Inf	Inf	17981	7554
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	10980	Inf	Inf	Inf	Inf	11556	Inf	Inf	Inf	Inf	14880
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	158	1389	2351	4727	Inf	1026	1990	2402	2893	Inf	10084	10552	13814	6217
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1232	2194	4570	Inf	1258	2221	2634	3107	Inf	10315	10783	14046	6431
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	962	3338	Inf	Inf	1237	1650	1876	Inf	Inf	Inf	13062	5200
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2376	Inf	Inf	Inf	1697	914	Inf	Inf	Inf	13109	4238
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	576	Inf	Inf	Inf	Inf	3900
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	282	1246	1658	2149	Inf	9340	9808	13070	5473
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	964	1376	1867	Inf	9058	9526	12788	5191
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	413	904	Inf	Inf	Inf	11825	4228
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	491	Inf	Inf	Inf	11412	3815
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	3324
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	468	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	612
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.11: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to mean maximum temperatures 19-21c.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	7612	466	1000	1571	2018	14816	1432	2453	3810	3863	15508	2864	3792	4746	6916	19522	3513	4710	5657	7044	Inf	4882	5280	5551	5846	Inf	12740	13412	12796	13498
B2	Inf	0	501	1036	1606	2054	7205	611	1632	2989	3899	7896	2042	2971	3924	6952	11910	2692	3889	4836	6223	Inf	4060	4459	4730	5024	Inf	11919	12591	11975	12677
B3	Inf	Inf	0	534	1105	1552	Inf	966	1988	3344	3398	Inf	2398	3326	4280	6451	Inf	3048	4244	5191	6579	Inf	4416	4814	5086	5380	Inf	12274	12946	12331	13033
B4	Inf	Inf	Inf	0	571	1018	Inf	Inf	2530	3886	2863	Inf	Inf	6624	7578	5916	Inf	Inf	7542	8489	9877	Inf	Inf	8113	8384	8678	Inf	Inf	Inf	15629	16331
B5	Inf	Inf	Inf	Inf	0	448	Inf	Inf	Inf	5713	2293	Inf	Inf	Inf	29374	5346	Inf	Inf	Inf	36178	32776	Inf	Inf	Inf	38069	34338	Inf	Inf	Inf	45314	46016
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1845	Inf	Inf	Inf	Inf	4898	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	413	1434	2791	8897	691	897	1825	2779	7727	4705	1547	2743	3690	5078	Inf	2915	3313	3585	3879	Inf	10773	11445	10830	11532
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1021	2378	8484	Inf	1432	2360	3314	8262	Inf	2081	3278	4225	5612	Inf	3450	3848	4119	4414	Inf	11308	11980	11364	12066
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1357	7463	Inf	Inf	4095	5049	9997	Inf	Inf	5013	5960	7347	Inf	Inf	5583	5854	6148	Inf	Inf	Inf	13099	13801
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	6106	Inf	Inf	Inf	23661	9159	Inf	Inf	Inf	30465	27063	Inf	Inf	Inf	32357	28625	Inf	Inf	Inf	39602	40304
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	3053	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	206	1134	2088	7036	4014	855	2052	2999	4386	Inf	2224	2622	2893	3188	Inf	10082	10754	10138	10840
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	928	1882	6830	Inf	650	1846	2793	4180	Inf	2018	2416	2688	2982	Inf	9876	10548	9933	10635
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	954	5902	Inf	Inf	918	1865	3252	Inf	Inf	1488	1759	2054	Inf	Inf	Inf	9004	9706
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	4948	Inf	Inf	Inf	6804	3402	Inf	Inf	Inf	8696	4964	Inf	Inf	Inf	15941	16643
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	455	1662	2609	3996	Inf	632	1641	1912	2207	Inf	8490	9162	9157	9859
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1207	2154	3541	Inf	1368	1777	2048	2342	Inf	9227	9899	9293	9995
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	947	2334	Inf	Inf	570	841	1136	Inf	Inf	Inf	8086	8788
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1387	Inf	Inf	Inf	1892	705	Inf	Inf	Inf	9137	9839
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1562	Inf	Inf	Inf	Inf	36194
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	234	1243	1515	1809	2340	3420	4092	8760	9462
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1009	1281	1575	Inf	7858	8530	8526	9228
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	271	565	Inf	Inf	Inf	7516	8218
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	294	Inf	Inf	Inf	7245	7947
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	34632
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1080	1752	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	672	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	702
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.12: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to mean maximum temperatures >21c.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	818	550	1710	1966	3105	16346	2024	8295	4671	3769	Inf	2988	3777	4803	5847	Inf	3752	4686	5077	5874	Inf	5412	9474	5936	6317	Inf	Inf	Inf	Inf	Inf
B2	Inf	0	558	1719	1975	3113	15528	2032	8303	4679	3778	Inf	2997	3785	4812	5855	Inf	3761	4694	5086	5883	Inf	5421	9482	5944	6326	Inf	Inf	Inf	Inf	Inf
B3	Inf	Inf	0	1161	1417	2555	Inf	1474	7745	4121	3220	Inf	2439	3227	4254	5297	Inf	3203	4137	4528	5325	Inf	4863	8925	5386	5768	Inf	Inf	Inf	Inf	Inf
B4	Inf	Inf	Inf	0	256	1395	Inf	Inf	6619	2960	2059	Inf	Inf	7963	8990	4136	Inf	Inf	12841	9264	4395	Inf	Inf	17629	10122	7131	Inf	Inf	Inf	Inf	Inf
B5	Inf	Inf	Inf	Inf	0	1139	Inf	Inf	Inf	2705	1803	Inf	Inf	Inf	Inf	3881	Inf	Inf	Inf	Inf	4139	Inf	Inf	Inf	Inf	6875	Inf	Inf	Inf	Inf	Inf
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	3035	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	945	7216	8829	Inf	Inf	1910	2698	3725	10005	Inf	2674	3608	3999	4796	Inf	4334	8396	4857	5239	Inf	Inf	Inf	Inf	Inf
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	6271	7884	Inf	Inf	965	1753	2780	9060	Inf	1729	2663	3054	3851	Inf	3389	7451	3912	4294	Inf	Inf	Inf	Inf	Inf
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1613	Inf	Inf	Inf	1344	2371	2789	Inf	Inf	6222	2645	3047	Inf	Inf	11010	3503	3885	Inf	Inf	Inf	Inf	Inf
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	1176	Inf	Inf	Inf	Inf	1434	Inf	Inf	Inf	Inf	4170	Inf	Inf	Inf	Inf	Inf
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	389	1177	2204	Inf	Inf	486	1420	2290	3087	Inf	2146	6208	3149	3530	Inf	Inf	Inf	Inf	Inf
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	788	1815	Inf	Inf	764	1698	2089	2886	Inf	2424	6486	2947	3329	Inf	Inf	Inf	Inf	Inf
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1027	Inf	Inf	Inf	4878	1301	2098	Inf	Inf	9666	2159	2541	Inf	Inf	Inf	Inf	Inf
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	2556	3353	Inf	Inf	Inf	3414	3796	Inf	Inf	Inf	Inf	Inf
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	258	Inf	Inf	Inf	Inf	2994	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	257	1191	2061	2859	Inf	1917	5979	2920	3301	Inf	Inf	Inf	Inf	Inf
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	934	1804	2601	Inf	1660	5722	2663	3044	Inf	Inf	Inf	Inf	Inf
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	871	1668	Inf	Inf	4788	1729	2111	Inf	Inf	Inf	Inf	Inf
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	797	Inf	Inf	Inf	858	1240	Inf	Inf	Inf	Inf	Inf
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	2736	Inf	Inf	Inf	Inf	Inf
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	7182	7707	8175	Inf	Inf	Inf	Inf	Inf
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	525	993	Inf	Inf	Inf	Inf	Inf
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	468	Inf	Inf	Inf	Inf	Inf
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.13: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to track speeds 0-40MPH.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	976	366	1616	1988	2350	8784	1512	2838	3851	7282	Inf	2507	3019	4765	7786	Inf	3087	6111	Inf	Inf	Inf	3406	3776	4013	4117	Inf	Inf	Inf	Inf	Inf
B2	Inf	0	476	1726	2098	2460	Inf	1622	2948	3961	7392	Inf	2617	3129	4875	7896	Inf	3197	6221	Inf	Inf	Inf	3516	3886	4123	4227	Inf	Inf	Inf	Inf	Inf
B3	Inf	Inf	0	1250	1622	1984	Inf	1146	2472	3485	6916	Inf	2141	2653	4399	7420	Inf	2721	5745	Inf	Inf	Inf	3040	3410	3647	3751	Inf	Inf	Inf	Inf	Inf
B4	Inf	Inf	Inf	0	371	734	Inf	Inf	2724	2724	5666	Inf	Inf	16908	6972	6170	Inf	Inf	20400	Inf	Inf	Inf	Inf	Inf	20688	20792	Inf	Inf	Inf	Inf	Inf
B5	Inf	Inf	Inf	Inf	0	362	Inf	Inf	Inf	24624	5294	Inf	Inf	Inf	28872	5798	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	4932	Inf	Inf	Inf	Inf	5436	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	216	1542	2555	Inf	Inf	1211	1723	3469	Inf	Inf	1791	4815	Inf	Inf	Inf	2110	2480	2717	2821	Inf	Inf	Inf	Inf	Inf
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1326	2339	Inf	Inf	995	1507	3253	Inf	Inf	1575	4599	Inf	Inf	Inf	1894	2264	2501	2605	Inf	Inf	Inf	Inf	Inf
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1013	Inf	Inf	Inf	14184	5261	Inf	Inf	Inf	17676	Inf	Inf	Inf	Inf	Inf	17964	18068	Inf	Inf	Inf	Inf	Inf
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	4248	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	504	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	288	800	2546	Inf	Inf	869	3893	Inf	Inf	Inf	1187	1558	1794	1898	Inf	Inf	Inf	Inf	Inf
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	512	2258	Inf	Inf	581	3605	Inf	Inf	Inf	899	1270	1506	1610	Inf	Inf	Inf	Inf	Inf
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1746	Inf	Inf	Inf	3492	Inf	Inf	Inf	Inf	Inf	3780	3884	Inf	Inf	Inf	Inf	Inf
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	3024	Inf	Inf	Inf	318	689	926	1029	Inf	Inf	Inf	Inf	Inf
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	288	392	Inf	Inf	Inf	Inf	Inf
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	648	752	Inf	Inf	Inf	Inf	Inf
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	936	Inf	Inf	Inf	Inf	Inf
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	371	607	711	Inf	Inf	Inf	Inf	Inf
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	237	340	Inf	Inf	Inf	Inf	Inf
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	104	Inf	Inf	Inf	Inf	Inf
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.14: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to track speeds 40-75MPH.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	4272	530	1179	1492	2017	7248	1521	2575	3216	3121	9822	2301	3140	4988	6950	Inf	3164	3475	5275	6296	Inf	4614	4433	4736	5037	Inf	6392	Inf	Inf	13857
B2	Inf	0	661	1311	1623	2148	2976	585	1639	2280	3253	5550	1365	2205	4053	6015	Inf	2228	2539	4339	5361	Inf	3678	3497	3800	4101	Inf	5456	Inf	Inf	12921
B3	Inf	Inf	0	649	962	1487	Inf	991	2045	2686	2591	Inf	1771	2610	4458	6420	Inf	2634	2944	4744	5766	Inf	4084	3903	4206	4507	Inf	5862	Inf	Inf	13327
B4	Inf	Inf	Inf	0	313	837	Inf	Inf	2827	3468	1942	Inf	Inf	7099	8947	10909	Inf	Inf	8947	10747	10255	Inf	Inf	10027	10331	10632	Inf	Inf	Inf	Inf	19452
B5	Inf	Inf	Inf	Inf	0	525	Inf	Inf	Inf	5748	1629	Inf	Inf	Inf	20292	15444	Inf	Inf	Inf	22254	17028	Inf	Inf	Inf	23814	17604	Inf	Inf	Inf	Inf	26424
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1105	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	468	1522	2163	3779	2574	1248	2087	3935	5897	Inf	2111	2421	4221	5243	Inf	3561	3380	3683	3984	Inf	5339	Inf	Inf	12804
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1054	1695	3311	Inf	780	1619	3467	5429	Inf	1643	1953	3753	4775	Inf	3093	2912	3215	3516	Inf	4871	Inf	Inf	12336
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	641	2257	Inf	Inf	4272	6120	8082	Inf	Inf	6120	7920	7428	Inf	Inf	7200	7503	7804	Inf	Inf	Inf	Inf	16624
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1616	Inf	Inf	Inf	14544	9696	Inf	Inf	Inf	16506	11280	Inf	Inf	Inf	18066	11856	Inf	Inf	Inf	Inf	20676
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	193	1033	2881	4843	Inf	1056	1367	3167	4189	Inf	2507	2325	2628	2929	Inf	4284	Inf	Inf	11749
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	840	2688	4650	Inf	863	1174	2974	3996	Inf	2313	2132	2435	2736	Inf	4091	Inf	Inf	11556
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1848	3810	Inf	Inf	1848	3648	3156	Inf	Inf	2928	3231	3532	Inf	Inf	Inf	Inf	12352
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1962	Inf	Inf	Inf	1962	1308	Inf	Inf	Inf	3522	1884	Inf	Inf	Inf	Inf	10704
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1584	Inf	Inf	Inf	Inf	2160	Inf	Inf	Inf	Inf	10980
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	288	599	2399	4739	Inf	1152	1557	1860	2161	Inf	2930	Inf	Inf	10981
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	311	2111	4451	Inf	1450	1269	1572	1873	Inf	3228	Inf	Inf	10693
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1800	4140	Inf	Inf	1080	1383	1684	Inf	Inf	Inf	Inf	10504
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2340	Inf	Inf	Inf	1560	246	Inf	Inf	Inf	Inf	9066
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	576	Inf	Inf	Inf	Inf	9396
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	264	857	1160	1461	Inf	2042	Inf	Inf	10281
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	593	896	1197	Inf	1778	Inf	Inf	10017
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	303	604	Inf	Inf	Inf	Inf	9424
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	301	Inf	Inf	Inf	Inf	9121
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	8820
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.15: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to track speeds 75-100MPH.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	2928	507	1205	1587	1844	6960	1929	3271	3807	6752	Inf	2573	3430	19575	4792	Inf	3890	4988	3909	4852	Inf	4576	5234	4499	4906	Inf	Inf	Inf	Inf	Inf
B2	Inf	0	872	1570	1951	2208	4032	1613	2955	3490	7116	Inf	2256	3114	19258	4476	Inf	3573	4671	3592	4536	Inf	4259	4917	4182	4589	Inf	Inf	Inf	Inf	Inf
B3	Inf	Inf	0	698	1080	1336	Inf	1422	2764	3299	6244	Inf	2066	2923	19067	4285	Inf	3382	4480	3402	4345	Inf	4068	4727	3991	4398	Inf	Inf	Inf	Inf	Inf
B4	Inf	Inf	Inf	0	382	638	Inf	Inf	4415	4415	5546	Inf	Inf	5218	20183	5400	Inf	Inf	7612	5696	5535	Inf	Inf	8996	6286	6693	Inf	Inf	Inf	Inf	Inf
B5	Inf	Inf	Inf	Inf	0	257	Inf	Inf	Inf	11294	5165	Inf	Inf	Inf	27062	12279	Inf	Inf	Inf	Inf	12414	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	4908	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	381	1723	2258	10142	Inf	1024	1881	18026	3243	Inf	2341	3439	2360	3303	Inf	3027	3685	2950	3357	Inf	Inf	Inf	Inf	Inf
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1342	1877	9761	Inf	644	1501	17645	2863	Inf	1960	3058	1980	2923	Inf	2646	3305	2569	2976	Inf	Inf	Inf	Inf	Inf
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	535	8419	Inf	Inf	803	16303	1521	Inf	Inf	3197	1282	1656	Inf	Inf	4581	1871	2279	Inf	Inf	Inf	Inf	Inf
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	7884	Inf	Inf	Inf	15768	986	Inf	Inf	Inf	Inf	1121	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	166	1023	Inf	Inf	Inf	1482	2580	1502	2445	Inf	2168	2827	2091	2498	Inf	Inf	Inf	Inf	Inf
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	857	Inf	Inf	Inf	1317	2415	1336	2279	Inf	2003	2661	1926	2333	Inf	Inf	Inf	Inf	Inf
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	2394	479	1422	Inf	Inf	3778	1068	1476	Inf	Inf	Inf	Inf	Inf
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2160	Inf	Inf	Inf	Inf	2295	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	135	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	144	1242	1784	2727	Inf	830	1489	1633	2041	Inf	Inf	Inf	Inf	Inf
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1098	1640	2583	Inf	686	1345	1489	1897	Inf	Inf	Inf	Inf	Inf
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	542	1485	Inf	Inf	1384	1131	1538	Inf	Inf	Inf	Inf	Inf
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	943	Inf	Inf	Inf	590	997	Inf	Inf	Inf	Inf	Inf
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	216	874	1019	1426	Inf	Inf	Inf	Inf	Inf
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	658	803	1210	Inf	Inf	Inf	Inf	Inf
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	145	552	Inf	Inf	Inf	Inf	Inf
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	407	Inf	Inf	Inf	Inf	Inf
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	792	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	72
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.16: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to track speeds 100-130MPH.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	1473	317	1892	2515	3191	35832	1664	1900	3988	4983	Inf	3497	4218	5100	6940	Inf	4424	5982	4860	5438	Inf	5983	7432	7900	7260	Inf	Inf	Inf	Inf	Inf
B2	Inf	0	549	2125	2748	3423	37908	1547	1783	3871	5216	Inf	3380	4102	4984	6823	Inf	4308	5866	4743	5321	Inf	5866	7315	7783	7143	Inf	Inf	Inf	Inf	Inf
B3	Inf	Inf	0	1576	2198	2874	Inf	1347	1583	3671	4666	Inf	3180	3902	4784	6623	Inf	4108	5666	4543	5121	Inf	5666	7115	7583	6943	Inf	Inf	Inf	Inf	Inf
B4	Inf	Inf	Inf	0	623	1298	Inf	Inf	2552	4640	3091	Inf	Inf	5684	6566	7592	Inf	Inf	7448	6326	6904	Inf	Inf	9220	9662	8726	Inf	Inf	Inf	Inf	Inf
B5	Inf	Inf	Inf	Inf	0	676	Inf	Inf	Inf	6442	2468	Inf	Inf	Inf	9394	9394	Inf	Inf	Inf	12094	9731	Inf	Inf	Inf	15694	12683	Inf	Inf	Inf	Inf	Inf
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1792	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	441	677	2765	Inf	Inf	1764	2486	3368	5717	Inf	2692	4250	3127	3705	Inf	4250	5699	6167	5527	Inf	Inf	Inf	Inf	Inf
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	236	2324	Inf	Inf	1833	2555	3437	5276	Inf	2761	4319	3196	3774	Inf	4319	5768	6236	5596	Inf	Inf	Inf	Inf	Inf
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2088	Inf	Inf	Inf	3132	4014	5040	Inf	Inf	4896	3773	4352	Inf	Inf	6667	7110	6173	Inf	Inf	Inf	Inf	Inf
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	2952	2952	Inf	Inf	Inf	5652	3290	Inf	Inf	Inf	9252	6242	Inf	Inf	Inf	Inf	Inf
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	216	938	1820	Inf	Inf	1144	2702	1579	2157	Inf	2702	4151	4619	3979	Inf	Inf	Inf	Inf	Inf
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	722	1604	Inf	Inf	928	2486	1363	1941	Inf	2486	3935	4403	3763	Inf	Inf	Inf	Inf	Inf
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	882	Inf	Inf	Inf	1764	641	1220	Inf	Inf	3535	3978	3041	Inf	Inf	Inf	Inf	Inf
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	2700	338	Inf	Inf	Inf	6300	3290	Inf	Inf	Inf	Inf	Inf
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	72	2254	2807	3407	Inf	1630	3079	3547	3812	Inf	Inf	Inf	Inf	Inf
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2182	2735	3335	Inf	1558	3007	3475	3740	Inf	Inf	Inf	Inf	Inf
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	554	1154	Inf	Inf	1771	2214	2479	Inf	Inf	Inf	Inf	Inf
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	600	Inf	Inf	Inf	3600	2400	Inf	Inf	Inf	Inf	Inf
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	2952	Inf	Inf	Inf	Inf	Inf
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	396	Inf	Inf	Inf	Inf
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1449	1917	2182	Inf	Inf	Inf	Inf	Inf
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	468	733	Inf	Inf	Inf	Inf	Inf
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	265	Inf	Inf	Inf	Inf	Inf
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	864
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.17: Minimum MTTF to the nearest whole month between condition states when considering underbridges.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	2761	442	1163	1547	1861	8656	1596	2228	2815	3829	17314	2515	3440	5003	6695	Inf	3500	4158	4821	6198	Inf	4483	5176	5411	5523	Inf	11364	14964	Inf	29247
B2	Inf	0	597	1317	1701	2016	5896	1049	1682	2269	3983	14554	1969	2894	4457	6149	Inf	2954	3612	4275	5652	Inf	3937	4630	4865	4977	Inf	10818	14418	Inf	28701
B3	Inf	Inf	0	720	1105	1419	Inf	1153	1785	2373	3387	Inf	2073	2998	4560	6253	Inf	3057	3716	4379	5755	Inf	4041	4734	4969	5081	Inf	10922	14522	Inf	28805
B4	Inf	Inf	Inf	0	385	699	Inf	Inf	3514	4102	2666	Inf	Inf	6103	7666	7981	Inf	Inf	6821	7484	8721	Inf	Inf	7927	8162	8186	Inf	Inf	Inf	Inf	31910
B5	Inf	Inf	Inf	Inf	0	314	Inf	Inf	Inf	7868	2282	Inf	Inf	Inf	18644	11747	Inf	Inf	Inf	20906	12487	Inf	Inf	Inf	22099	14629	Inf	Inf	Inf	Inf	38353
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1967	Inf	Inf	Inf	Inf	14117	Inf	Inf	Inf	Inf	14857	Inf	Inf	Inf	Inf	16999	Inf	Inf	Inf	Inf	40723
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	255	887	1475	3271	8658	1174	2099	3662	5354	Inf	2159	2817	3480	4857	Inf	3142	3835	4070	4182	Inf	10023	13623	Inf	27906
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	632	1220	3016	Inf	919	1844	3407	5099	Inf	1904	2562	3226	4602	Inf	2887	3580	3815	3927	Inf	9768	13368	Inf	27651
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	588	2384	Inf	Inf	2589	4152	4467	Inf	Inf	3307	3970	5207	Inf	Inf	4413	4648	4672	Inf	Inf	Inf	Inf	28396
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1796	Inf	Inf	Inf	10776	3879	Inf	Inf	Inf	13038	4619	Inf	Inf	Inf	14231	6761	Inf	Inf	Inf	Inf	30485
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	12150	Inf	Inf	Inf	Inf	12890	Inf	Inf	Inf	Inf	15032	Inf	Inf	Inf	Inf	38756
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	181	1106	2669	4608	Inf	1166	1824	2487	3864	Inf	2149	2842	3077	3189	Inf	9030	12630	Inf	26913
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	925	2488	4427	Inf	985	1643	2306	3683	Inf	1968	2661	2896	3008	Inf	8849	12449	Inf	26732
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1563	3502	Inf	Inf	718	1382	2758	Inf	Inf	1824	2059	2083	Inf	Inf	Inf	Inf	25807
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1939	Inf	Inf	Inf	2262	1234	Inf	Inf	Inf	3455	2964	Inf	Inf	Inf	Inf	26688
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	740	Inf	Inf	Inf	Inf	2882	Inf	Inf	Inf	Inf	26606
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	199	902	1565	2942	Inf	1182	1875	2110	2267	Inf	8063	11663	Inf	25991
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	703	1367	2743	Inf	983	1676	1911	2068	Inf	7864	11464	Inf	25792
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	664	2040	Inf	Inf	1106	1341	1365	Inf	Inf	Inf	Inf	25089
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1376	Inf	Inf	Inf	1193	702	Inf	Inf	Inf	Inf	24426
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	2142	Inf	Inf	Inf	Inf	25866
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	332	1025	1260	1521	2988	7213	10813	Inf	25245
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	693	928	1189	Inf	6881	10481	Inf	24913
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	235	496	Inf	Inf	Inf	Inf	24220
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	261	Inf	Inf	Inf	Inf	23985
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	23724
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	3600	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	720
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.18: Minimum MTTF to the nearest whole month between condition states when considering overbridges.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	3209	412	1145	1753	2954	13541	1513	2949	4072	6250	14572	2960	4113	4832	8174	17902	3769	5343	6270	7614	Inf	5099	6129	6658	7212	Inf	14315	15251	12520	12749
B2	Inf	0	379	1112	1720	2921	10332	705	2141	3263	5980	11363	2152	3305	4024	7366	14693	2961	4535	5462	6806	Inf	4291	5321	5850	6403	Inf	13507	14443	11712	11941
B3	Inf	Inf	0	733	1341	2542	Inf	1101	2537	3659	5838	Inf	2548	3701	4420	7762	Inf	3357	4931	5858	7202	Inf	4687	5717	6246	6800	Inf	13903	14839	12108	12337
B4	Inf	Inf	Inf	0	608	1809	Inf	Inf	3126	4249	5104	Inf	Inf	5813	6532	9018	Inf	Inf	8631	9559	10903	Inf	Inf	9417	9946	10500	Inf	Inf	Inf	15808	16038
B5	Inf	Inf	Inf	Inf	0	1201	Inf	Inf	Inf	6696	4497	Inf	Inf	Inf	20918	8410	Inf	Inf	Inf	26975	28319	Inf	Inf	Inf	29429	28040	Inf	Inf	Inf	35291	34730
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	4557	Inf	Inf	Inf	Inf	8470	Inf	Inf	Inf	Inf	41014	Inf	Inf	Inf	Inf	41851	Inf	Inf	Inf	Inf	48541
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	568	2004	3126	5843	1031	1287	2440	3160	6501	4361	1636	3210	4137	5481	Inf	2966	3996	4525	5079	Inf	12182	13118	10387	10617
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1436	2558	5275	Inf	1446	2600	3319	6661	Inf	2256	3830	4757	6101	Inf	3586	4616	5145	5698	Inf	12802	13738	11007	11236
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1122	3839	Inf	Inf	2687	3406	6748	Inf	Inf	5505	6432	7776	Inf	Inf	6291	6820	7374	Inf	Inf	Inf	12682	12912
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2717	Inf	Inf	Inf	14222	6630	Inf	Inf	Inf	20279	21623	Inf	Inf	Inf	22733	21344	Inf	Inf	Inf	28595	28034
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	3913	Inf	Inf	Inf	Inf	36457	Inf	Inf	Inf	Inf	37294	Inf	Inf	Inf	Inf	43984
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	256	1410	2129	5471	3330	605	2179	3106	4450	Inf	1935	2965	3494	4048	Inf	11151	12087	9356	9586
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1154	1873	5215	Inf	809	2383	3310	4654	Inf	2139	3169	3698	4252	Inf	11355	12291	9560	9790
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	719	4061	Inf	Inf	2818	3745	5089	Inf	Inf	3604	4133	4687	Inf	Inf	Inf	9995	10225
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	3342	Inf	Inf	Inf	6057	7401	Inf	Inf	Inf	8511	7122	Inf	Inf	Inf	14373	13812
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	32544	Inf	Inf	Inf	Inf	33381	Inf	Inf	Inf	Inf	40070
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	377	1951	2878	4222	Inf	766	1897	2426	2980	Inf	9982	10918	8288	8518
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1574	2501	3845	Inf	1330	2360	2889	3443	Inf	10546	11482	8751	8980
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	927	2271	Inf	Inf	786	1315	1869	Inf	Inf	Inf	7177	7406
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1344	Inf	Inf	Inf	2454	1065	Inf	Inf	Inf	8316	7755
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	837	Inf	Inf	Inf	Inf	7526
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	206	1337	1866	2420	3348	4140	5076	7728	7957
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1131	1660	2214	Inf	9216	10152	7522	7751
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	529	1083	Inf	Inf	Inf	6391	6621
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	554	Inf	Inf	Inf	5862	6092
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	6689
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	792	1728	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	936	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	230
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.19: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to track speeds <3.5 EMGTPA.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	2133	439	948	1526	1875	10935	1472	2598	3297	3245	13419	2698	3720	6708	4811	Inf	3544	3894	4860	5222	Inf	4420	4968	5134	5343	Inf	9622	Inf	Inf	Inf
B2	Inf	0	838	1347	1925	2274	8802	952	2078	2777	3644	11286	2178	3200	6188	4715	Inf	3024	3374	4340	5118	Inf	3900	4448	4614	4823	Inf	9102	Inf	Inf	Inf
B3	Inf	Inf	0	509	1087	1436	Inf	1032	2159	2858	2806	Inf	2259	3281	6269	4372	Inf	3104	3455	4421	4783	Inf	3981	4529	4694	4904	Inf	9183	Inf	Inf	Inf
B4	Inf	Inf	Inf	0	578	927	Inf	Inf	3090	3789	2297	Inf	Inf	4278	7266	3863	Inf	Inf	7266	5772	4274	Inf	Inf	9198	7716	7926	Inf	Inf	Inf	Inf	Inf
B5	Inf	Inf	Inf	Inf	0	349	Inf	Inf	Inf	12078	1719	Inf	Inf	Inf	17892	3285	Inf	Inf	Inf	Inf	3696	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1370	Inf	Inf	Inf	Inf	2936	Inf	Inf	Inf	Inf	3347	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	355	1482	2181	4506	2484	1582	2603	5591	4119	Inf	2427	2778	3744	4521	Inf	3304	3851	4017	4226	Inf	8506	Inf	Inf	Inf
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1127	1826	4151	Inf	1227	2248	5236	3764	Inf	2072	2423	3389	4166	Inf	2949	3496	3662	3871	Inf	8151	Inf	Inf	Inf
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	699	3024	Inf	Inf	1188	4176	2637	Inf	Inf	4176	2682	3048	Inf	Inf	6108	4626	4835	Inf	Inf	Inf	Inf	Inf
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2326	Inf	Inf	Inf	5814	1938	Inf	Inf	Inf	Inf	2349	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1566	Inf	Inf	Inf	Inf	1977	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	238	1259	4247	6101	Inf	1083	1434	2400	3177	Inf	1960	2507	2673	2882	Inf	7162	Inf	Inf	Inf
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1022	4010	5864	Inf	845	1196	2162	2940	Inf	1722	2270	2435	2644	Inf	6924	Inf	Inf	Inf
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2988	4842	Inf	Inf	2988	1494	2272	Inf	Inf	4920	3438	3647	Inf	Inf	Inf	Inf	Inf
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1854	Inf	Inf	Inf	Inf	2265	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	411	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	90	441	1407	2184	Inf	720	1268	1433	1643	Inf	5922	Inf	Inf	Inf
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	351	1317	2094	Inf	877	1424	1590	1799	Inf	6079	Inf	Inf	Inf
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	966	1744	Inf	Inf	1932	2098	2307	Inf	Inf	Inf	Inf	Inf
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	778	Inf	Inf	Inf	1944	2153	Inf	Inf	Inf	Inf	Inf
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	396	944	1109	1319	Inf	5598	Inf	Inf	Inf
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	548	713	923	Inf	5202	Inf	Inf	Inf
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	166	375	Inf	Inf	Inf	Inf	Inf
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	209	Inf	Inf	Inf	Inf	Inf
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.20: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to track speeds 3.5-12.0 EMGTPA.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	2870	626	1663	1969	2417	5588	1419	2760	3505	5629	Inf	2335	3017	5357	7753	Inf	3052	3268	3926	4800	Inf	3819	3942	4320	4248	Inf	5792	6296	Inf	8964
B2	Inf	0	337	1373	1680	2127	2718	966	2307	3053	5177	Inf	1882	2564	4904	7301	Inf	2600	2815	3473	4347	Inf	3367	3489	3867	3795	Inf	5340	5844	Inf	8511
B3	Inf	Inf	0	1036	1343	1790	Inf	793	2134	2879	5003	Inf	1709	2391	4731	7127	Inf	2426	2641	3300	4174	Inf	3193	3316	3694	3622	Inf	5166	5670	Inf	8338
B4	Inf	Inf	Inf	0	306	754	Inf	Inf	2643	2643	4767	Inf	Inf	6867	8979	6891	Inf	Inf	7118	7776	8650	Inf	Inf	7956	8334	8098	Inf	Inf	Inf	Inf	12814
B5	Inf	Inf	Inf	Inf	0	448	Inf	Inf	Inf	6305	8429	Inf	Inf	Inf	Inf	10553	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	16794	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	690	2031	2776	4900	Inf	1606	2288	4628	7024	Inf	2323	2539	3197	4071	Inf	3090	3213	3591	3519	Inf	5063	5567	Inf	8235
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1341	2086	4210	Inf	916	1598	3938	6334	Inf	1633	1849	2507	3381	Inf	2400	2523	2901	2829	Inf	4373	4877	Inf	7545
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	745	2869	Inf	Inf	4224	6336	4993	Inf	Inf	4475	5133	6007	Inf	Inf	5313	5691	5455	Inf	Inf	Inf	Inf	10171
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2124	Inf	Inf	Inf	Inf	4248	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	212	1008	3348	6012	Inf	930	1259	1917	2792	Inf	1697	1820	2198	2239	Inf	3670	4174	Inf	6955
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	796	3136	5800	Inf	717	1047	1705	2579	Inf	1485	1607	1985	2027	Inf	3457	3961	Inf	6743
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2340	5004	Inf	Inf	251	909	1783	Inf	Inf	1089	1467	1231	Inf	Inf	Inf	Inf	5947
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	2664	Inf	Inf	Inf	888	888	Inf	Inf	Inf	2928	1210	Inf	Inf	Inf	Inf	5926
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	552	1943	2601	3475	Inf	1319	1442	1820	2089	Inf	3292	3796	Inf	6805
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1391	2049	2923	Inf	767	890	1268	1537	Inf	2740	3244	Inf	6253
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	658	1533	Inf	Inf	838	1216	980	Inf	Inf	Inf	Inf	5696
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	874	Inf	Inf	Inf	2040	322	Inf	Inf	Inf	Inf	5038
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	960	Inf	Inf	Inf	Inf	5676
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	261	941	1319	1588	Inf	2234	2738	Inf	6304
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	680	1058	1327	Inf	1973	2477	Inf	6043
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	378	647	Inf	Inf	Inf	Inf	5363
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	269	Inf	Inf	Inf	Inf	4985
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	4716
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	504	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	360
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

Table C.21: Minimum MTTF to the nearest whole month between condition states when considering bridges exposed to track speeds >12.0 EMGTPA.

From,To	A1	B2	B3	B4	B5	B6	C2	C3	C4	C5	C6	D2	D3	D4	D5	D6	E2	E3	E4	E5	E6	F2	F3	F4	F5	F6	G2	G3	G4	G5	G6
A1	0	1806	323	1982	2352	2867	18062	2743	3003	4071	4413	Inf	3317	3896	5348	7763	Inf	4839	5916	4354	5771	Inf	6531	6813	4822	5103	Inf	Inf	Inf	Inf	Inf
B2	Inf	0	1010	2669	3040	3554	38376	1476	1736	2804	5100	Inf	2050	2629	4081	6497	Inf	3573	4650	3088	4504	Inf	5265	5547	3556	3836	Inf	Inf	Inf	Inf	Inf
B3	Inf	Inf	0	1659	2030	2544	Inf	2420	2680	3748	4091	Inf	2994	3573	5025	7441	Inf	4517	5594	4032	5448	Inf	6209	6491	4500	4780	Inf	Inf	Inf	Inf	Inf
B4	Inf	Inf	Inf	0	371	885	Inf	Inf	3952	3952	2431	Inf	Inf	6621	8073	7645	Inf	Inf	8799	7080	8221	Inf	Inf	10599	7548	7828	Inf	Inf	Inf	Inf	Inf
B5	Inf	Inf	Inf	Inf	0	514	Inf	Inf	Inf	6821	2061	Inf	Inf	Inf	11990	10513	Inf	Inf	Inf	Inf	11089	Inf	Inf	Inf	Inf	13753	Inf	Inf	Inf	Inf	Inf
B6	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	1547	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
C2	Inf	Inf	Inf	Inf	Inf	Inf	0	333	593	1661	14585	Inf	907	1486	2938	5354	Inf	2430	3507	1945	3361	Inf	4122	4404	2413	2693	Inf	Inf	Inf	Inf	Inf
C3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	260	1328	14252	Inf	574	1153	2605	5021	Inf	2097	3174	1612	3028	Inf	3789	4071	2080	2360	Inf	Inf	Inf	Inf	Inf
C4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1068	13992	Inf	Inf	2669	4121	4760	Inf	Inf	4847	3128	4544	Inf	Inf	6647	3596	3876	Inf	Inf	Inf	Inf	Inf
C5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	12924	Inf	Inf	Inf	5170	3693	Inf	Inf	Inf	Inf	4269	Inf	Inf	Inf	Inf	6933	Inf	Inf	Inf	Inf	Inf
C6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
D2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	134	713	2165	Inf	Inf	1657	2734	1172	2588	Inf	3349	3631	1640	1920	Inf	Inf	Inf	Inf	Inf
D3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	579	2031	Inf	Inf	1523	2599	1038	2454	Inf	3215	3497	1506	1786	Inf	Inf	Inf	Inf	Inf
D4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1452	Inf	Inf	Inf	2178	459	1875	Inf	Inf	3978	927	1207	Inf	Inf	Inf	Inf	Inf
D5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf	423	Inf	Inf	Inf	Inf	3087	Inf	Inf	Inf	Inf	Inf
D6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	576	Inf	Inf	Inf	Inf	3240	Inf	Inf	Inf	Inf	Inf
E2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	216	1293	1841	6053	Inf	1908	2190	2309	2589	Inf	Inf	Inf	Inf	Inf
E3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	1077	1625	5837	Inf	1692	1974	2093	2373	Inf	Inf	Inf	Inf	Inf
E4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	548	4760	Inf	Inf	1800	1016	1296	Inf	Inf	Inf	Inf	Inf
E5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	4212	Inf	Inf	Inf	468	749	Inf	Inf	Inf	Inf	Inf
E6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	2664	Inf	Inf	Inf	Inf	Inf
F2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	432	Inf	Inf	Inf	Inf
F3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	920	1300	1580	Inf	Inf	Inf	Inf	Inf
F4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	379	660	Inf	Inf	Inf	Inf	Inf
F5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	281	Inf	Inf	Inf	Inf	Inf
F6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf	Inf
G2	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf	Inf
G3	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf	Inf
G4	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	Inf	Inf
G5	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0	720
G6	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf	0

C.2 Detailed Imperfect Inspections Outputs

Table C.22: Table containing the probabilities for the maintenance actions from each condition state when considering imperfect inspections.

Condition State	Probability of Maintenance			
	No Repair	Minor Repair	Major Repair	Replacement
A1	1.00	0.00	0.00	0.00
B2	0.00	1.00	0.00	0.00
B3	0.00	0.80	0.20	0.00
B4	0.00	0.40	0.60	0.00
B5	0.00	0.20	0.80	0.00
B6	0.00	0.00	1.00	0.00
C2	0.00	0.80	0.20	0.00
C3	0.00	0.63	0.37	0.00
C4	0.00	0.37	0.63	0.00
C5	0.00	0.25	0.75	0.00
C6	0.00	0.00	0.80	0.20
D2	0.00	0.40	0.60	0.00
D3	0.00	0.37	0.63	0.00
D4	0.00	0.25	0.75	0.00
D5	0.00	0.37	0.63	0.00
D6	0.00	0.00	0.60	0.40
E2	0.00	0.20	0.80	0.00
E3	0.00	0.25	0.75	0.00
E4	0.00	0.00	0.63	0.37
E5	0.00	0.00	0.37	0.63
E6	0.00	0.00	0.20	0.80

Table C.22: Table containing the probabilities for the maintenance actions from each condition state when considering imperfect inspections.

Condition State	Probability of Maintenance			
	No Repair	Minor Repair	Major Repair	Replacement
F2	0.00	0.00	0.60	0.40
F3	0.00	0.00	0.50	0.50
F4	0.00	0.00	0.37	0.63
F5	0.00	0.00	0.12	0.88
F6	0.00	0.00	0.00	1.00
G2	0.00	0.00	0.67	0.33
G3	0.00	0.00	0.40	0.60
G4	0.00	0.00	0.20	0.80
G5	0.00	0.00	0.00	1.00
G6	0.00	0.00	0.00	1.00

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