RAILROAD DECISION SUPPORT TOOLS FOR TRACK MAINTENANCE

BY

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DISSERTATION

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ABSTRACT

The North American rail system requires billions of dollars annually to be maintained in proper working order. Therefore, it is critical that maintenance is performed on the right components, at the right time, and in the right location. Application of decision support tools that use objective analysis methods can result in more efficient and effective maintenance plans. This requires quantifying both direct costs associated with the performance of maintenance and the indirect costs of train delay, disruption risk, and equipment routing. To thoroughly assess these costs, an integrated approach is needed that incorporates degradation modeling, project selection, and maintenance scheduling for the entire track structure. Planning track maintenance in this way allows for the effects of changing maintenance timing to be seen explicitly through the disruption risk while considering equipment and other constraints. Managers can then combine the output from the decision support tools with their practical experience to account for location- or situation-specific characteristics that are not easily quantifiable.

This dissertation presents new methods for determining the indirect costs associated with both planned and unplanned disruptions. Train delay cost models were developed that consider train operating characteristics such as terminal dwell and trainset configurations. These costs were combined with a train delay calculator adapted from the highway domain to determine the operational impact to trains during both disrupted and recovery operations. Degradation models were also developed or modified to estimate unplanned disruption risk for slow orders and acute disruptions such as rail breaks and derailments. Combined, these new methods allow for the costs of unplanned disruptions to be estimated and accounted for when planning track maintenance.

A maintenance plan costing model was developed that incorporates the direct and indirect costs associated with a proposed maintenance plan. The model determines the complete cost of the plan based on capital maintenance timing, level of maintenance aggregation, and detour use. Incorporation of maintenance aggregation allows for the efficiencies of performing multiple maintenance activities simultaneously on long work windows to be explicitly considered. Alternative maintenance plans that adjust a base schedule to use maintenance aggregation can be compared to determine if the reduced direct and delay costs outweigh the additional indirect costs. Since the best way to modify a plan to reduce costs is not always obvious and can be tedious to determine manually, an optimization model was developed and solved using simulated annealing. While optimality is not guaranteed when using simulated annealing, it was shown to provide lower cost maintenance plans.

To Kate, Anna, Peter, and Rachel

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Most importantly I need to express gratitude to my God, who gives me the strength to persevere.

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CHAPTER 1.
INTRODUCTION

1.1 Study purpose

The primary purpose of this research is to develop decision support tools for railroad track maintenance planning. These tools will provide maintenance personnel with objective guidance to evaluate maintenance timing alternatives and enable more cost-effective decisions.

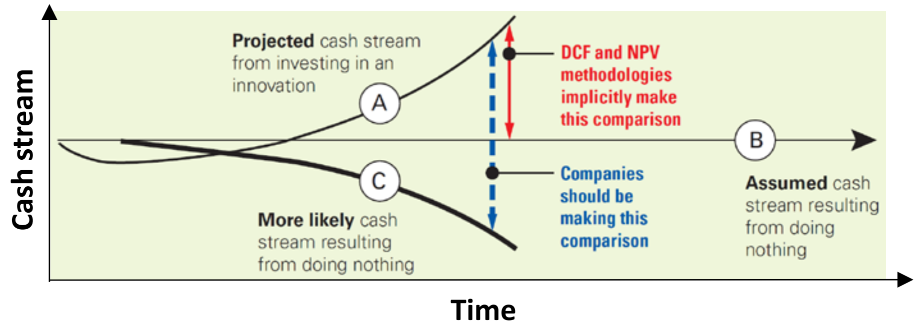
1.2 Background and research motivation

Ensuring efficient and effective railroad operations requires that all aspects of the system be kept in proper working order. North American railroads spend billions of dollars each year on track maintenance to achieve this (Association of American Railroads 2017). With expenditures of this magnitude, even incremental improvements in maintenance planning or execution can result in substantial savings or the ability to complete more projects. In general, using objective methods to evaluate management decisions have been shown to improve outcomes, especially when the most efficient alternative is not obvious (Davenport & Harris 2007). This is especially true in track maintenance planning where interactions within both the track structure and the railroad network can make it difficult to identify the optimal project set. The methods I develop in this dissertation inform decision support tools that can quickly consider multiple alternatives to recommend a maintenance plan. Managers can combine their qualitative knowledge of the system with the recommendations from the decision support tools to develop a more efficient final plan. In this dissertation, I describe several new tools that can be used for objective maintenance planning and an optimization model that integrates them.

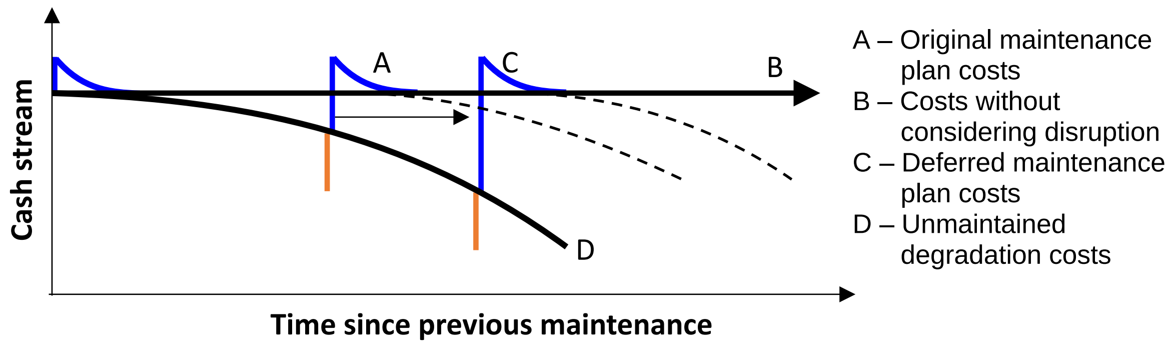
This research also advances the theoretical understanding of how maintenance decisions affect the total cost of track ownership and operation. These costs will be greatly affected by the maintenance plan. Direct costs (e.g. labor, equipment, and material) are explicitly incurred when performing maintenance. These are typically tracked by railroads and can be determined on a per unit basis. Direct costs are normally considered in maintenance analysis because they are readily available; however, indirect costs are not always included and are harder to quantify. Indirect costs are secondary effects of either performing or deferring maintenance and consist of train delay impacts and disruption risk. Train delay can be further divided into line delay and network effects, although these are not always treated separately. Line delay is from trains on the disrupted line, while network effects are incurred on other parts of the network, including adjacent lines and rail yards. A model to estimate disruption-caused line delay is discussed in Chapter 5.

Disruption risk is the expected cost of unplanned service disruptions, e.g. accidents or slow orders, and decreases when track maintenance is performed. Over time, the disruption risk will increase until maintenance is performed again, so deferring maintenance activity will eventually increase this risk. The relationship between track maintenance and disruption risk is not well understood, and in this dissertation, I explore how it can be approximated using currently available data. Operational benefits may also accrue due to improved track condition, but insufficient information is available to quantify them at this point.

Most maintenance personnel have a qualitative understanding that deferring maintenance increases disruption risk. This is closely related to a relatively new concept developed to reflect the costs of deferring information technology investments, termed the direct cash flow (DCF) trap (Figure 1.1a) (Christensen et al. 2008). I modified this concept and applied it to railroad



a)



b)

Figure 1.1: Direct cash flow (DCF) trap a) original concept (Christensen et al. 2008) b) modified for railroad track maintenance

track maintenance using disruption risk as the cost of deferring maintenance (Figure 1.1b). While the DCF trap concept is not the primary focus of this dissertation, it provides a conceptual framework to visualize the effects of maintenance timing and balance direct and indirect costs. Visualization can enhance maintenance personnel's understanding of how disruption risk changes based on maintenance timing. Quantifying this risk will provide additional perspective and a metric for how changing maintenance schedules affects traffic disruptions on a section of track. This will also enable better theoretical analysis of how to balance maintenance efficiency and effectiveness with traffic impacts. Improved understanding of these relationships may influence how maintenance thresholds are determined to improve safety while further reducing the total cost of track ownership.

1.3 Objective and scope

Without an objective method to compare the indirect effects of maintenance, it would be difficult to effectively evaluate the best time, location, and method for it to occur. Decision support tools that use objective metrics will allow management to effectively evaluate the total cost of their decisions. This is especially true when deferring maintenance since the additional cost of disruptions can be difficult to estimate but may outweigh the perceived benefits. Quantifying the relationship between disruption risk and maintenance timing allows these costs and benefits to be compared and provide more effective planning.

This research will focus on maintenance planning in the context of North American freight railroads. They have a number of characteristics that differ from most other rail systems in the world. They are privately owned, vertically integrated, and substantial portions of their network are single track with passing sidings. North American railroads are particularly focused on economic efficiently, so costs and benefits are the primary metrics in this study. Vertical integration means that all costs are incurred by the same organization, so both track maintenance and traffic disruption costs must be included in the analysis. The primarily single-track network complicates this because closing a track for maintenance prevents trains from using that route. While the North American rail network allows for rerouting onto other lines or railroads, these options may not be available or cost effective. This dissertation introduces simplified methodologies for considering re-routing and double track sections to show their application, but they will not be addressed in detail. This scope will limit this research’s applicability in some international contexts that operate on highly structured timetables or with multiple main tracks.

Based on the above objectives and scope, the main research questions addressed in this dissertation are:

- How to effectively assess and account for the cost of slow orders and other traffic disruptions (Chapters 3, 5, and 6).
- How to adequately consider the risk of traffic disruptions when evaluating a maintenance plan (Chapters 4, 6, and 7).
- How to balance disruption risk against the benefits of schedule modification (Chapters 7, 8, and 9).
- How to minimize the total cost of a network maintenance plan (Chapter 9).

1.4 Dissertation organization and research summary

This dissertation consists of eight body chapters (Figure 1.2), each with specific objectives for development of the holistic maintenance plan costs. In general, each chapter builds on the

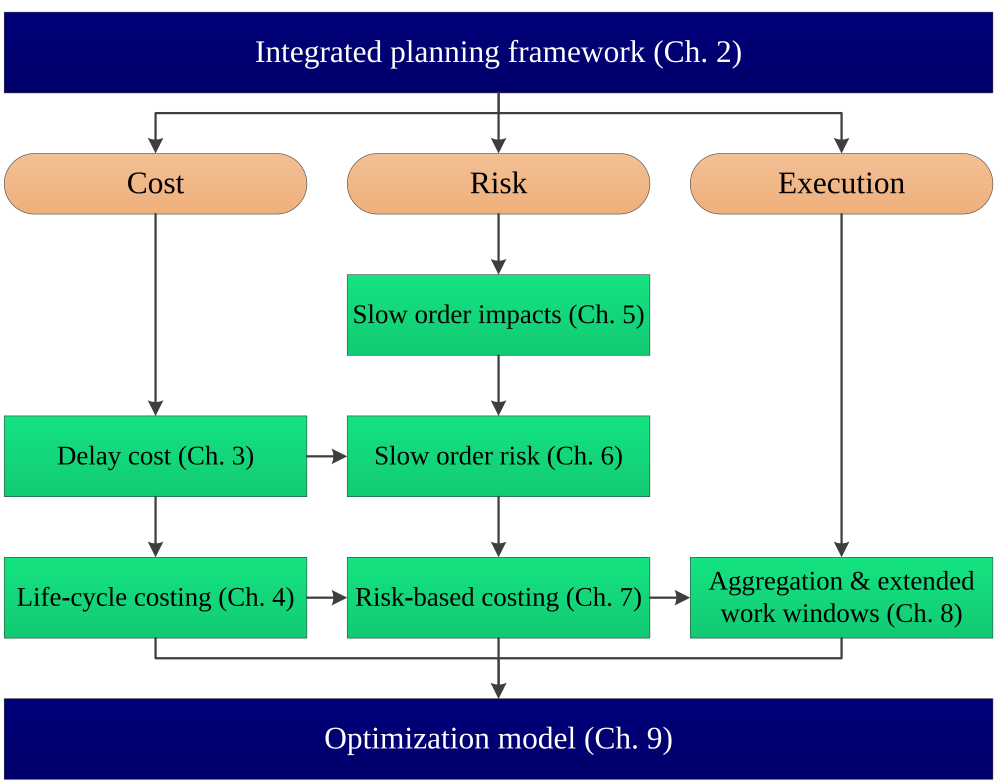


Figure 1.2: Dissertation structure

previous ones to develop a comprehensive understanding of the costs associated with a maintenance plan.

Chapter 2 presents an overarching framework for how the track maintenance planning steps can be integrated so all the costs associated with a maintenance plan can be considered. Historically, track maintenance planning has been segmented into degradation, project selection, and scheduling for each of the major components. This chapter gives an overview of each step and explains how integrating the three planning steps for the entire track structure can provide more cost-effective decisions. Subsequent chapters will focus on tools for project selection since that appears to be the least developed of the three planning steps.

Chapter 3 describes a train delay costing model that can be used for a variety of applications. Train delay is not always considered in maintenance planning, but it can account for a substantial share of operating cost. Detailed methods to determine route- and train-type-specific delay costs are critical to ensuring that they are as accurate as possible. This analysis showed how route lengths, operating characteristics, and the amount of line delay influences train delay cost. A central finding is how terminal operations affect delay accumulation and when delay mitigation efforts would be most effective. Average costs from this chapter were used to evaluate train delay in the rest of this dissertation.

Chapter 4 presents an initial attempt to consider disruption costs in a planning framework. Rather than looking explicitly at maintenance timing, this analysis compared the life-cycle costs of timber and concrete crossties to identify the conditions where each material would be most cost effective. Component upgrades are one way to improve track performance, so this analysis is effectively a long-term comparison between maintenance alternatives. One observation from this analysis was that the slow-order costs were much lower than expected based on industry experience, so additional study into that cost category was pursued.

Chapter 5 presents a methodology for determining the impacts of traffic disruption since there does not appear to be an established closed-form method to estimate these impacts, particularly for slow orders. This methodology adapts concepts from road traffic analysis to calculate the cumulative train delay based on the normal operating and disruption characteristics. This approach allows delay to be calculated without simulations. This chapter also discusses the model sensitivity to input parameters and how probabilistic models can be used to determine average slow order train delay.

Chapter 6 builds on the work in Chapter 5 by developing a new approach using probabilistic models to estimate slow order costs as a function of time since capital maintenance was last performed. This chapter describes probabilistic models that were used to predict the occurrence of rail, crosstie, and ballast defects and their associated costs. This analysis showed how slow order costs vary over time and between components. It also shows the relationship between direct and delay costs and discusses insights on how to effectively reduce them.

Chapter 7 presents the development of a risk-based approach for track-maintenance costing. This model enhances the general framework from Chapter 4 by incorporating the models from Chapters 5 and 6 and adding a methodology for estimating the risk of acute disruptions, such as broken rails and accidents. The mathematical formulation allows maintenance planners to see the cost effects of plan changes. This analysis also shows the importance of including all applicable costs and establishing the correct planning period to prevent inaccurate comparisons.

Chapter 8 expands the model from Chapter 7 to include the effects of maintenance aggregation on long work windows and the possibility of detours. Aggregating maintenance on long work windows provides economies associated with improved efficiency and reduced track time but frequently requires adjusting maintenance schedules. This is a problem because changing when maintenance is performed will result in either reduced component utilization or increased disruption risk. Including slow orders and acute disruptions allows schedule adjustment costs to be balanced against maintenance aggregation benefits. Since detours can allow traffic to continue flowing when a track is removed from service, considering them provides a more reasonable maintenance disruption cost estimate. This analysis showed the benefits of aggregating track maintenance on elongated work windows and how they vary based on how aggregation is implemented.

Chapter 9 further expands the mathematical model to include double track territories and applies a metaheuristic to optimize the track maintenance plan for a system. While the mathematical model allows evaluation of a given maintenance plan, it would be inefficient and time consuming to evaluate multiple routes and optimize the maintenance schedule manually. The sub-model complexity makes it difficult to apply a commercial solver to the problem, so a metaheuristic was used to adjust a base schedule and find a near-optimal solution. This approach can allow for substantial savings off the base schedule with limited manual effort.

Each chapter of this dissertation provides specific insights on how to quantify the costs associated with maintenance or unplanned disruptions. While each can be beneficial on their own, the greatest benefit will be achieved when they are used together because the track system can be evaluated holistically. This will allow decision makers to plan maintenance for all track components on an entire network in a manner that effectively balances maintenance needs and service quality.

1.5 Contribution summary

As will be discussed in Chapter 2, there are several aspects of track maintenance planning including the individual track components and the various steps in the process. This dissertation will focus on improving maintenance project selection since that appears to be the area with the greatest potential for improvement. The main area where this research will contribute to the state of the art is by integrating indirect costs into the maintenance-planning process, specifically maintenance-related delay and disruption risk. Since accurate train-delay costs are required to realize either of these benefits, this dissertation also advances the state of the art by presenting a methodology to calculate delay costs based on train operating characteristics. Topic-specific literature reviews are included in each chapter, so this section will focus on a broader look at how this research improves the state of the art in maintenance planning.

When train delay is considered in the context of track maintenance, it is usually focused on planning specific maintenance activities and adjusting train schedules to accommodate them. This is especially true in research for networks where a precise timetable is used (Higgins et al. 1999; Albrecht et al. 2013; Forsgren et al. 2013; Lidén & Joborn 2016, 2017; Vansteenwegen et al. 2016). While this approach is important for determining precise maintenance timing, it is most beneficial after specific maintenance projects have been selected, so the impacts can be modeled in a detailed fashion. It is also less applicable in the North American freight railroad context where train schedules are relatively flexible (Mussanov et al. 2017; Shih et al. 2017).

Another approach in the literature is to negate train delay because maintenance is either performed on lines with low volumes or at times when there is no traffic (Simson et al. 2000; Martland 2008; Zhang et al. 2013). While this may be applicable on certain predominantly passenger or low-volume freight lines, the greatest need for optimized maintenance planning in North America is on high tonnage main lines where delay costs can be substantial. A shortcoming of many of these models is the lack of consideration for post-maintenance slow orders and cascading delays. Zoeteman (2001) includes post-maintenance slow orders but neglects cascading delays, and he states that a dedicated simulation tool would be required to estimate these effects. The model described in Chapter 5 overcomes these shortcomings by estimating train delay for track outages and slow orders in a closed form. This allows train delay to be considered during project selection without detailed simulations. The consideration of maintenance-caused delay costs is expanded in Chapters 8 and 9, where adjustments to consider rerouting and multiple track territory are discussed to give a more complete view of maintenance disruption costs.

Another area where this research contributes to the state of the art is consideration of unplanned disruptions. Some models discuss them without detailing their costs or explicitly accounting for them (Famurewa et al. 2015). Others account for unplanned disruptions through a penalty cost for degraded conditions but do not explain how it would be calculated (Zhao et al. 2006; Zhang et al. 2013). Without details of how to calculate the penalty costs, a maintenance planner would be unable to effectively quantify the impact of a disruption. Simson et al. (2000) presents a methodology to address slow orders but assumes that trains are short enough to only encounter one at a time. This assumption would often be incorrect in North America where relatively long trains increase the likelihood that a train would be affected by multiple slow orders simultaneously. Zoeteman (2004) considers the direct component of unplanned maintenance costs and post-maintenance speed restrictions but not defect-caused slow orders or accidents. This may be because European railway networks are largely passenger focused and have stricter train schedules. Therefore, they have a lower tolerance for service disruptions and are willing to have more preventative maintenance to ensure train operations proceed according to plan. Despite flexible operations, service disruptions, particularly slow orders, are a substantial concern for North American railroads, so it would be unreasonable to neglect their impacts. The delay model in Chapter 5 and the acute disruption costing methodology in Chapter 7 overcome these shortcomings to include disruption risk in maintenance project selection.

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CHAPTER 2.

AN INTEGRATED MODEL FOR THE EVALUATION AND PLANNING OF RAILROAD TRACK MAINTENANCE[1]

2.1 Introduction

The track maintenance planning process has historically been treated as distinct steps with each track component managed separately (Figure 2.1a). Different levels of management evaluate each step for each major element of the track system, e.g. rail, crossties, and ballast. Due to this segmented process, maintenance may be performed on a component because funds are available even if it is not the most effective way to improve the overall track condition. The framework proposed here integrates the maintenance planning steps in a new way to allow for more cost-effective maintenance decisions (Figure 2.1b).

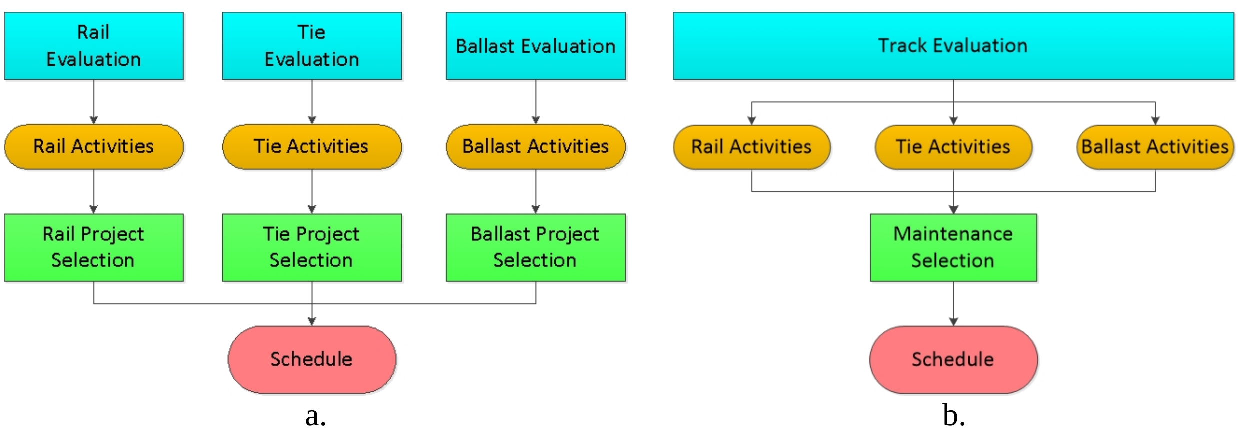

Figure 2.1: Maintenance planning methodologies a) traditional maintenance planning b) proposed maintenance planning framework

[1] This chapter is modified from Lovett, A.H., C.P.L. Barkan, and C.T. Dick. 2013. An integrated model for the evaluation and planning of railroad track maintenance. In: *Proceedings of the American Railway Engineering and Maintenance-of-Way Association Annual Conference*, Indianapolis, Indiana, September 2013, pp. 1029-1044.

The three general steps in track maintenance planning are track evaluation, maintenance selection, and project scheduling. Track evaluation is the process of determining the track quality to identify maintenance needs. Maintenance selection consists of evaluating either individual projects or a complete maintenance plan to determine what work to perform. Project scheduling consists of determining when each planned activity will be performed to ensure the plan is feasible and maintenance crews are assigned efficiently. Integrating these three steps allows management to holistically compare maintenance alternatives and quantify the potential effects of deferring maintenance. In order to understand how to plan maintenance effectively, it helps to understand the ways it can occur.

Maintenance can be performed either reactively or proactively, known respectively as corrective and preventive maintenance. Corrective maintenance consists of waiting until a component has failed and then repairing or replacing it (Granström 2005, 2008). A track failure is defined in this dissertation as a specified tolerance being exceeded or an acute failure, such as a broken rail. Either will disrupt service by stopping or slowing trains and result in costly delays. Additionally, acute failures can result in derailments with potentially severe consequences. Corrective maintenance has the benefit of ensuring that all of the component's utility has been used by deferring maintenance as long as possible. This can result in increased costs because of the above-mentioned disruptions and the fact that, since it is unknown exactly when a component will fail, maintenance crews may need to be dispatched at a time when they are not prepared or convenient to the area. Corrective maintenance is unavoidable to an extent but should be minimized due to these additional costs.

Alternately, preventive maintenance consists of using a plan to maintain components before they fail. This could consist of either a predetermined cycle or thresholds to indicate maintenance should be performed in the near future (Granström 2005, 2008). Preventive maintenance can be up to 80 percent less expensive than corrective maintenance (Granström 2005) and has the potential to improve planning so work is performed when it is most convenient and cost effective. Preventive maintenance may also result in premature component replacement and increased costs from maintenance being performed more frequently than necessary. Current railroad practice is a combination of both approaches. Preventive, or capital, maintenance restores the track condition, while corrective, or ordinary, maintenance keeps it above a minimum threshold. Capital maintenance has also been found to be more efficient than ordinary maintenance due to economies of scale (Grimes & Barkan 2006).

Advanced preventive, or predictive, maintenance planning can improve procedures by using models to estimate the future track condition and determine when maintenance can most effectively be performed (Wireman 2008). This approach seeks to realize the full benefits of preventive and corrective maintenance by scheduling maintenance activities to balance the amount of premature maintenance against the failure risk. This chapter will discuss the current state-of-the-art in each planning step and a framework that can be used for track maintenance planning.

2.2 Framework overview

While research has been performed on parts of the maintenance planning process, an extensive literature review did not reveal any comprehensive models covering the entire maintenance planning process from predicting track condition to detailed scheduling. Some frameworks have integrated the track evaluation and maintenance selection steps, but they focus more on identifying when track components will exceed a maintenance threshold (Zarembski

1991; Uzarski & McNeil 1994). Adjustments would need to be made to include disruption risk in the analysis. Considering the entire planning process is important because the track system is part of a network. The interrelated nature of the rail system means that performing maintenance on a track component will affect how other components in the same track section perform. It also means that resource constraints may prevent that same type of maintenance from being performed in another part of the network. An integrated planning approach allows for these interactions to be explicitly considered.

In this chapter, I present an integrated track maintenance planning (ITMP) framework that can be used to make decisions based on a comprehensive view of the entire maintenance planning process. It is comprised of three modules representing each major planning step. The modular framework enables consideration of the entire process while allowing the individual modules to be updated without significantly affecting the rest of the model. The remainder of this chapter provides more detail about the individual modules and describes how the framework can be implemented.

2.3 Track evaluation

The first step of the track maintenance planning process is to determine the track condition during the maintenance-planning period. This may include degradation models, projections based on trend data, established intervals, rules of thumb, or maintenance personnel’s intuition and experience. An ideal evaluation tool would be a degradation model capable of considering a wide range of parameters including operating conditions, the existing track condition, and maintenance history. Track degradation can be considered either by looking at the components separately or considering track component interactions. There are many models that represent individual track component degradation (MacLean 1957; Wells 1982; Reiner & Staplin 1983; Davis 1987; Chrismer 1988; Martland & Auzmendi 1990; Acharya 1994; Chrismer & Selig 1994; Kumar 2006; Garnham et al. 2007; Walton-Macaulay et al. 2014; Qian et al. 2014), but the components do not exist in isolation (Hay 1982). Integrated models allow for a more comprehensive look at how the track performs (Hay 1982; Ferreira & Murray 1997; Zhang et al. 1997, 2000). For example, track with fouled ballast has a lower track modulus and results in higher rail bending stresses and accelerated fatigue (American Railway Engineering and Maintenance-of-Way Association 2012). If the model only looks at rail fatigue, improving the ballast condition may not be reflected in condition predictions, and maintenance such as grinding or rail replacement may be performed prematurely.

Beyond the differences of viewing the track system on a component or system level, different methods can be used to model track degradation including mechanistic and empirical modeling. Mechanistic modeling considers the actual physical interactions within materials or at component interfaces that cause degradation. This method can be computationally intensive and time consuming as materials are not homogeneous and the component interactions may be difficult to measure or are poorly understood. Alternately, empirical modeling is statistical in nature and uses historical data. Two major drawbacks of empirical modeling are that the relationships are only as good as the input data and not all combinations of input parameters may be found in the historical record. The optimal method for degradation modeling is a combination of both that allows for some consideration of the physical properties of the track structure while taking into account the statistical variation of how degradation will occur (Arthur D. Little Inc. 1992).

Many industries have shifted to mechanistic-empirical modeling including pharmaceutical (Yamashita & Hashida 2003), chemical reactor (Duarte et al. 2004), and highway design (Roesler & Hiller 2013). Specifically, AASHTO's Pavement ME software analyzes the mechanistic aspects of pavement degradation based on the expected loading while considering material behavior variation (Roesler & Hiller 2013). Similar methods can be applied to the track structure since there is inherent variability in the track component life. Although some failure mechanisms are fairly well understood, further investigation is needed to determine the factors that cause them (Lamson & Dowdall 1985; Cannon & Pradier 1996; Indraratna et al. 1998; Cannon et al. 2003; da Silva et al. 2003; Zeman et al. 2009). Whichever method is selected for modeling track degradation, specific focus should be given to the track parameters that have the possibility of disrupting service, such as FRA track class specifications or potential derailment risks such as rail flaws.

There are also some common statistical distributions to predict component life. The Weibull distribution has frequently been used to model component degradation and failure rates, including all major track structure components (MacLean 1957; Orringer 1990; Shyr & Ben-Akiva 1996; Lim et al. 2004; Kumar 2006; Jeong & Gordon 2009; Modarres et al. 2017). The Weibull distribution is advantageous due to its simplicity and limited number of parameters (Equation 2.1). The shape factor, α, determines how sinusoidal the distribution is, and the scale factor, β, is related to the average failure interval and determines distribution spread. As will be discussed further in Chapter 6, the Weibull parameters can be functions of input variables to consider variable operating situations (Mishalani & Madanat 2002; Kleinbaum & Klein 2012). This is one way that the physical interactions could be integrated into an empirical model. The exponential and Rayleigh distributions are two other common component life models, but they are special cases of the Weibull (Modarres et al. 2017). Other distributions may have a better fit but would need to be evaluated based on available data.

$$F(t) = 1 - \exp(-(t/\beta)^{\alpha}) \qquad 2.1$$

Where:

α = shape factor
β = scale factor (MGT or years)
x = component age (MGT or years)

Big data techniques are another approach to predicting track maintenance needs. These methods analyze large unstructured datasets and extract relationships directly from the data without making assumptions about its nature (Davenport et al. 2012; McAfee & Brynjolfsson 2012; Davenport & Kim 2013). Since some mechanistic relationships may be difficult to represent, these techniques could allow them to be estimated using operating parameters and track measurements. Big data analysis has been explored for many railroad applications and could be beneficial for future development (Kaewunruen 2014; Nunez & Attoh-Okine 2014; Núñez et al. 2014; Carr 2015; Clark 2015; Thaduri et al. 2015; Kalay 2015; Pace 2015; Pace & Kontokostas 2015; Palese 2015; Rice 2015).

Data to develop degradation models can come from a variety of sources, including both manual and automated inspections. Most railroads use data from track geometry and rail defect inspection vehicles, and at least one railroad uses high-speed cameras with machine vision to monitor track conditions (Clouse et al. 2006; Sawadisavi et al. 2008; Carr et al. 2009; Wanek-Libman 2012, 2014). These provide information that can be directly linked to track components for maintenance evaluation. Some railroads have also started using vehicle/track interaction (VTI) sensors on rolling stock to monitor track conditions (Hicks & Stevens 2009; Clark et al. 2015; Cowie et al. 2015; Crump et al. 2015). These measurements can be used for predicting when track maintenance should be performed, but they may not be as helpful in determining what maintenance activities would best improve the track condition. If this could be overcome, VTI measurement data could be a viable source of data for degradation modeling due to the near continuous monitoring they provide and possible relationship to derailment risk.

2.4 Maintenance selection

The maintenance selection module uses degradation information to either evaluate a defined maintenance plan or select which projects should be completed in a given year. The limited research published on this topic in the rail sector has focused on the use of degradation models to determine when to conduct maintenance, rather than project selection explicitly (see references in Section 2.3). Research has been performed on related elements in other fields. For example, in highway infrastructure planning, research has been done on optimizing what maintenance should be performed and when (Ouyang & Madanat 2004; Ouyang 2007; Gu et al. 2012), but it does not appear that work has been published on optimizing the maintenance of multiple components. Therefore, some general evaluation criteria and approaches were examined.

Two common methodologies used in investment decisions are to calculate the net present value (NPV) and internal rate of return (IRR). NPV has a long history of use in the railroad industry since it was pioneered by Arthur Wellington in the late 1800's to evaluate how timing influences revenues and investments (Dulman 1989). These methods, especially IRR, rely on having positive revenues to determine if a project is satisfactory, and both are sensitive to the selected discount rate (Ross et al. 2013). NPV can be applied to maintenance planning by discounting the costs and finding the least cost plan. It is important to include disruption costs in the analysis to avoid the DCF trap (see Chapter 1).

Another method that is increasingly being used in transportation project evaluation is cost-benefit analysis (CBA). This method evaluates the costs and benefits of a potential project to determine its suitability. The output is commonly reported as the benefit to cost (B/C) ratio. CBA is commonly used when determining the impact of social projects, where the benefit is derived from a reduction in future costs (Andersson et al. 2004; Bryan et al. 2007; Vatn 2008; Australian Rail Track Corporation 2010; Landau et al. 2015). CBA was used by Liu et al. (2010) to evaluate the cost effectiveness of track class upgrades, and it could also be applicable for maintenance activities because there are no additional revenues associated with the decision, only decreases in cost. The benefit of a given maintenance project could be calculated as the disruption risk reduction associated with it. Risk is defined as the probability of an event multiplied by the event severity or consequence (Erkut & Verter 1998; Zhao et al. 2007), so the benefit is the reduction in the disruption probability multiplied by the expected incident cost. The costs would be those incurred during maintenance, including both the direct and delay costs. As all costs incurred will be experienced by the railroad, minimizing the maintenance plan cost using the NPV method would accomplish the same goal as CBA in a simpler manner.

Another common method used in similar transportation applications is case-based reasoning (CBR) (Jarmulak et al. 1997; Cui et al. 2005; Chou 2009). In CBR, the method that historically resulted in the least cost and best result is selected by comparing the current situation with a database of historical conditions and outcomes (Bengtsson 2004; Chou 2009). CBR could be beneficial for use in railroad track maintenance, as not every condition requires the same treatment. For example, a crosslevel problem may result from differential ballast settlement or a surface bent rail and require tamping or rail replacement respectively. For this distinction to be made, the database must contain the necessary historical condition and maintenance data. As maintenance is completed, the database grows and predictions will become more accurate. One shortcoming of CBR is the lack of data accessibility that prevents model development without railroad partnership. If the necessary data were available, big data techniques could also be used to find relationships between the track conditions and the maintenance cost.

Based on the options discussed here and the publically available data, using a modified NPV approach to compare the costs of different maintenance plans will be the simplest and most applicable option. If there are concerns over selecting the appropriate discount rate, a range of values could be used to determine if there are significant differences in the least cost plans. These discount rates should conform to standard practices to ensure they are reasonable and valid (Ross et al. 2013).

One of the most common methods for activity selection is the knapsack model, and it can be applied in the ITMP framework. With this model, projects are chosen to maximize benefits while constraining the cost and time requirements (Alanne 2004; Kellerer et al. 2004; Gabriel et al. 2006). In the rail industry, Lai (2008) used the knapsack model to select capacity improvement projects. For track maintenance, the criteria would need to be adjusted to minimize total costs, not just the cost to perform the selected maintenance activities, while constraining the direct maintenance costs to a budget. Constraints could be applied to exclude maintenance on track segments in good condition from consideration or requiring maintenance on track that has a high likelihood of a disruption. This should be accommodated by including disruption risk in the costing methodology, but if there are safety concerns with accident risk getting too high, a constraint could require maintenance when the accident rate exceeds a given threshold.

2.5 Project scheduling

Once the optimal project mix has been selected, they must be scheduled to ensure the most effective implementation. This is another area where substantial research has been performed. The track maintenance scheduling problem (TMSP) model as developed by Peng et al. (2011) is one that has beneficial characteristics. This model was specifically designed for the rail industry and minimized transportation costs while considering the effects of work windows, activity sequencing, and linear project clustering for a preselected set of projects. Previous attempts to address railroad maintenance scheduling have considered minimization of train disruptions (Higgins 1998; Higgins et al. 1999), minimization of maintenance costs including set-up and take-down times (Lake et al. 2002), consideration of job prioritization (Budai et al. 2006), and balancing the impacts of maintenance and when the activity needs to be completed (Cheung et al. 1999). Peng et al. (2011) improved on other large-scale TMSP models by considering travel costs and exact consideration of network distances.

It would be important to ensure that the scheduling model does not repeat aspects of the other modules, e.g. aggregation of maintenance or work window length. While this does not appear to be a problem with the Peng et al. TMSP model, it should be considered and may result in selection of a simpler project scheduling model. It may also be beneficial to have a simpler scheduling model in the ITMP framework that estimates crew and equipment routing costs while ensuring feasibility when developing the maintenance plan. A more complex and precise model could then be applied to determine exact project schedules.

2.6 Framework operation

The ITMP framework combines the three planning steps to determine the total cost of a given maintenance plan. Although it could be used to prioritize and select maintenance activities, evaluating pre-defined maintenance plans appears to be the best approach. This would be accomplished by using each module to calculate their associated costs (i.e. disruption, maintenance, or routing) for each year in the maintenance planning period. The project scheduling module will also verify the plan is feasible. Those costs would be discounted to compute the total cost of the maintenance plan. Combining the three maintenance-planning steps in this manner will allow for a more comprehensive and objective evaluation of potential maintenance plans.

Simply evaluating maintenance plans is not enough to develop an optimal one. Adjustments need to be made to determine if there are lower cost alternatives. It would be inefficient to adjust the maintenance plans for multiple routes manually while balancing budgets, equipment constraints, and disruption costs. This is especially true if the network is large. To resolve this, the ITMP framework could be integrated with an optimization model. This could develop a network-wide maintenance plan to balance the disruption, maintenance, and routing costs while meeting any necessary budgetary or equipment constraints. This approach will be expanded in Chapter 9.

It is anticipated that this model would be run more than once per planning period. As discussed in Chapters 7 and 8, when maintenance is deferred outside of the planning period those costs would be removed from the analysis even though they will still occur. Repeated application in a rolling horizon approach will allow those costs to be considered in the next run. This iterative approach would also allow for new information about the track condition to be considered as inspections and capital maintenance projects are performed. Planners may also want to use the model to determine the capital maintenance budget. The model can estimate the total cost of operations with multiple budgets to see if allowance for additional maintenance would reduce the overall costs.

2.7 Conclusions and future work

Integrating the track maintenance planning steps into a single framework can provide a holistic approach to track maintenance planning and the possibility to reduce costs. This is because the ITMP framework allows for quantitative comparisons between disruption and maintenance costs while explicitly considering resource constraints. In addition to the benefits of reducing costs, an improved understanding of track degradation will aid in budgeting decisions since planners will have a better understanding of when maintenance expenditures will need to be made.

Some of the potential future work has been described throughout the chapter, but there are specific areas where additional work is needed to further progress the framework applicability. Since the least amount of work appears to have been performed on maintenance project selection, that will be the focus of the remainder of this dissertation. Subsequent chapters will explore the development of train delay effects, disruption risk, cost models, and how to optimize the maintenance plan, but there is room for improvement on the other steps as well.

For degradation modeling, the identification or development of more advanced models will assist with making the maintenance-planning framework more robust and applicable. Models actively used by North American Class 1 railroads could be viable options since they would be validated and aligned with the needs of an operating railroad. If new railroad data could be acquired, it could be used to validate existing models or develop new ones specifically aligned to the needs of both railroads and the framework. New data analysis could also use big data techniques to generate more robust insights and relationships based on historical operations and maintenance data. For maintenance scheduling, further examination is needed to find or develop one that can both effectively schedule the activities but also work within the larger ITMP framework. While the Peng et al. (2011) TMSP model looks promising, it needs to be further evaluated to ensure that it can be fully integrated. A simpler model may be needed to allow the full optimization model to operate in a reasonable time and ensure it does not conflict with aspects considered in the other modules.

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CHAPTER 3.

DETERMINING FREIGHT TRAIN DELAY COSTS ON RAILROAD LINES IN NORTH AMERICA[1]

3.1 Introduction

Rail traffic disruptions and congestion create train delays that increase the operating cost of freight rail transportation. Quantifying the cost of these delays is important to justify investment in railroad infrastructure to relieve congestion. North American freight railroads typically own the track and operate the trains, so delay costs are considered internally. Therefore, it is difficult to obtain specific values for use with public projects or research. In some foreign rail systems, delay penalty costs are negotiated explicitly in contracts between train operators and rail infrastructure owners (Gibson et al. 2002).

In the early 20th century, North American delay costs were one dollar per train-minute payable by the contractor responsible for the delay (AREA Committee No. I 1904), but more recent estimates range from $200 to over $1,000 per train-hour (Smith et al. 1990; Federal Railroad Administration Railroad Safety Advisory Committee 1999; Schafer & Barkan 2008; Lai & Barkan 2009; Dingler et al. 2011; Schlake et al. 2011). Each of these approaches included different cost categories and none of them appear to have considered the impact of yards and terminals on delays. In some cases, the authors do not describe the methodology used to determine costs, making it difficult to update the values or apply them to specific operating scenarios.

[1] This chapter is modified from Lovett, A.H., C.T. Dick, and C.P.L. Barkan. 2015. Determining Freight Train Delay Costs on Railroad Lines in North America. In: *Proceedings of the International Association of Railway Operations Research (IAROR) 6th International Conference on Railway Operations Modelling and Analysis*, Tokyo, Japan, March 2015.

Train delays affect railroad operating costs in five general categories: crew, locomotives, fuel, railcars, and lost revenue (Schafer 2008; Dingler 2010). Depending on how freight trains are operated, these costs will accumulate differently when delays are encountered, and yards and terminals have the potential to either mitigate or exacerbate delay. This chapter provides a framework to determine the delay cost for three common types of freight trains, unit, manifest, and intermodal, that each accumulate such costs in different ways. Although the cost formulation here is for major North American freight railroads, it can be adapted for systems where the infrastructure owner is not the train operator as is common in some other parts of the world. Individual shipper-specific late fees are not considered in this analysis, as the costs involved will vary widely depending on particular contracts and thus are difficult to generalize.

3.2 Methodology

Unit, manifest, and intermodal freight trains all operate differently. The unique operational aspects of each type of train and their associated costs must be modeled differently to get a complete picture of the cost of train delay. Operational aspects must be considered in the calculation of train delay costs. These aspects include available buffer time at terminals, the probability of a railcar or locomotive missing its connection to the next train, or the number of trainsets needed for dedicated, or captive, service. This improves upon previous attempts to model train delay that isolated delay costs from other operational impacts (Schafer 2008; Dingler 2010; Schlake 2010). An isolated approach may be appropriate for irregular delay incidents, such as an accident or maintenance, but systematic delays due to regular meets and passes or planned stops between yards will affect how the whole system operates in the long term.

In North America, freight trains do not operate on rigid schedules based on a precise system-wide timetable. Train departure times from originating terminals have varying degrees of flexibility depending on the type of train and railroad business objectives. Without a fixed schedule, it is not possible to calculate train delay as the difference between the scheduled and actual arrival times at the final destination or a specific point along the route. Instead, it is common practice in North America to calculate freight train delay as the difference between the actual runtime between origin and destination, or over a route segment of interest, and the minimum runtime between these points (Martland 2008). The minimum runtime is calculated using a train performance calculator and represents the least amount of time required for the train to travel between origin and destination while obeying all permanent speed restrictions but without interference from other trains on the line. By this definition, train delay includes the additional time spent traveling on a route due to meets and passes with other trains and any other condition that causes a train to stop or otherwise travel below the maximum authorized speed.

The following sections develop equations that relate train delay to various freight railroad cost categories for the specific operating aspects of unit, manifest, and intermodal trains.

3.2.1 Unit trains

Unit trains carry a single type of freight, usually a bulk commodity, between the same origin and destination. In this way, they effectively work as a conveyor belt, moving goods from a source terminal to a consumption terminal without intermediate stops for “switching” to add, remove, or reorder railcars in the train. For example, a coal train may transport loaded railcars from a mine to a power plant and then return the empty railcars back to the same mine to be reloaded for the next trip back to the same power plant. Each such round trip is termed a “cycle.” Due to the lack of any specific data, this approach assumes the unit train experiences the same amount of delay on both legs of this cycle when determining the minimum runtime (Equation 3.1). Since returning empty railcars may have a lower priority and more delay, Equation 3.1 can be modified if average delay times for each leg are known.

$$T_T = 2(L_R/V + T_A + T_D) \tag{3.1}$$

Where:

- T_T – time a train is active (transporting, loading, or unloading freight) per cycle
- L_R – length of the route
- V – maximum allowable train speed
- T_A – average processing time at the origin and destination terminals
- T_D – delay time per leg

Cycle time may or may not be the limiting factor in determining the amount of freight that can be shipped between origin and destination. If the production or consumption rates are such that less than one train load of freight is produced or consumed over the duration of the unit train cycle, the trains may not be able to depart or be processed immediately. These inherent system delays act as an implicit buffer that mitigates the impact of train delay along the route. The maximum or desired shipment frequency based on contractual agreements for delivery intervals will determine the actual cycle that a train operates on and the number of trainsets needed for the service (Equation 3.2).

$$Q_T = \lceil T_T/T_{PT} \rceil \tag{3.2}$$

Where:

- Q_T – number of trainsets required for the service
- T_{PT} – average departure period or interval to a given location for the railcars
- Other variables as defined above

The operational cost of the unit train can be computed on a per-cycle basis. This approach includes the cost of all trains operating during the time between two subsequent departures of the same trainset from the same location (Equation 3.3).

$$C_P = Q_T(\lceil T_T, T_{PT} \rceil (C_L Q_L + C_C Q_C) + T_T(Q_L(C_O + C_F) + C_W)) \quad 3.3$$

Where:

- C_P – total train cost per cycle ($/cycle)
- $\lceil T_T, T_{PT} \rceil$ – cycle time, T_T rounded up to the next integer multiple of T_{PT}
- C_L – locomotive ownership cost ($/locomotive-hour)
- Q_L – number of locomotives per trainset
- C_C – car hire rate ($/car-hour)
- Q_C – number of railcars per trainset
- C_O – locomotive operating cost ($/locomotive-hour)
- C_F – fuel cost ($/locomotive-hour)
- C_W – crew wage ($/train-hour)

Other variables as defined above

The average hourly train delay cost can then be computed by dividing the cycle cost by the amount of delay per cycle and the number of trains. As noted above, the level of delay per cycle will be double the delay per leg, T_D, because each train travels the route twice (once in each direction) per cycle.

3.2.2 Manifest trains

In manifest freight train operations, the rolling stock is not assigned to dedicated service in a train between a single origin and destination. Railcars and locomotives are used on any route and are temporarily grouped together to form a manifest train operating between major classification yards as dictated by transportation demand. Upon arrival at the next yard, the railcars will be sorted again to make connections with different trains originating at the terminal and bound for various destinations. Each manifest train can be considered independently from other trains when calculating delay costs between yards, but each delayed train has a probability of either delaying a subsequent train or having its railcars miss their connection at the next yard. This analysis assumes that there are always sufficient crews and locomotives, so subsequent trains departing the destination yard will not need to wait for delayed inbound trains. Delayed railcars that miss connections will be rescheduled to the next eligible train.

In some instances, outbound trains may be delayed leaving a terminal because there are insufficient locomotives or crews available. In these cases, the outbound railcar ownership and revenue opportunity costs would need to be accounted for rather than the crew and locomotive ownership costs since they would be in continuous use.

Given the above assumptions, the delay cost of manifest trains operating between yards consists of three parts: the operating delay cost, the cost of locomotives missing their connection, and the cost of railcars missing their connection (Equations 3.4 – 3.9). Equations 3.8 and 3.9 are the locomotive and railcar PMAKE functions. The PMAKE concept was developed to represent the probability of a railcar or locomotive making its next scheduled connection based on the yard availability time and operational efficiency (Tykulsker 1981). The yard availability time is measured as the difference between the railcar or locomotive arrival time at the yard and the planned departure time of its connecting outbound train. While the PMAKE function can be any probability distribution, it is often represented as a uniform distribution based on the minimum time required to make a connection and the minimum time required to guarantee a connection (Tykulsker 1981; Martland 1982).

$$\begin{aligned} C_D = {} & T_D(Q_L(C_O + C_F) + C_W) \\ & + C_L Q_L T_{PL}(\lceil (T_D - T_{AL})/T_{PL} \rceil + 1 - P_L(T_L')) \\ & + (C_C + C_G')Q_C T_{PT}(\lceil (T_D - T_{AC})/T_{PT} \rceil + 1 - P_C(T_C')) \end{aligned} \qquad 3.4$$

$$C_G' = 2C_G P_A/(T_P P_R) \qquad 3.5$$

$$T_L' = T_{AL} - T_D + \lceil T_D - T_{AL}, T_{PL} \rceil \qquad 3.6$$

$$T_C' = T_{AC} - T_D + \lceil T_D - T_{AC}, T_{PT} \rceil \qquad 3.7$$

$$P_L(t) = \begin{cases} 1, & t > T_{LM} \\ \dfrac{t - T_{LC}}{T_{LM} - T_{LC}}, & T_{LC} \le t \le T_{LM} \\ 0, & else \end{cases} \qquad 3.8$$

$$P_C(t) = \begin{cases} 1, & t > T_{CM} \\ \dfrac{t - T_{CC}}{T_{CM} - T_{CC}}, & T_{CC} \le t \le T_{CM} \\ 0, & else \end{cases} \quad 3.9$$

Where:

C_D – delay cost per cycle ($/train-hour)
T_{PL} – average locomotive departure interval
T_{AL} – average planned yard availability for locomotives
T_L' – adjusted availability between a locomotive's arrival and the next eligible departure
$P_L(t)$ – locomotive PMAKE function
C_G' – lost revenue from railcar delay ($/car-hour)
T_{AC} – average planned yard availability for railcars
$P_C(t)$ – railcar PMAKE function
T_C' – adjusted availability between a railcar’s arrival and the next eligible departure
C_G – average revenue ($/car)
P_A – availability rate
T_P – cycle time
P_R – empty return ratio (ratio of total trips to loaded trips)
T_{LM} – amount of time when a locomotive to guaranteed to make the next connection
T_{LC} – minimum amount of time (cutoff) to switch a locomotive onto another train for on-time departure
T_{CM} – amount of availability for a railcar to guarantee the next connection
T_{CC} – minimum amount of time to switch a railcar onto the next train for an on-time departure
Other variables as defined above

The first term of Equation 3.4 includes the locomotive operations, fuel, and crew costs that only depend on delay incurred in transit, not yard operations. The second and third terms are for the locomotive and railcar delay respectively. As delay increases, the probability of a locomotive or railcar missing the planned connection will increase until it is not possible to make the connection. At that point, the locomotives and railcars will be assigned to the next eligible train based on locomotive requirements or train destination. The delay will not increase until the adjusted availability, T_L’, is less than the maximum guaranteed connection time, T_{LM}. If a railcar or locomotive has a long planned connection time, the delay in arriving at the yard only acts to shorten the connection time but not lengthen the overall trip time. In this way, the yard connection time acts as a buffer to absorb delay. If a railcar or locomotive has a short connection time, there is a higher probability that even a small delay in arriving at the yard will cause the railcar to miss its connection, greatly extending the overall trip time. In this manner, the yard connection time multiplies the original delay and its associated costs. This phenomenon will be demonstrated further in the case study. The revenue lost, C_G', is based on the methodology of Dingler (2010) and considers the actual revenue per car along with the amount of time the railcar is available for moving freight (Equation 3.5). As the potential for additional revenue from increased capacity decreases, C_G' will approach zero.

3.2.3 Intermodal trains

Intermodal trains use specialized railcars to transport containers and highway trailers between specialized loading and unloading facilities commonly referred to as intermodal terminals. From an operations perspective, intermodal trains have some characteristics of both unit and manifest trains. Intermodal trains often travel in dedicated service between two intermodal terminals. If containers or trailers are continuing by rail beyond the destination terminal of a given train, they are typically unloaded from an inbound railcar and repositioned by truck for loading onto an outbound train, rather than the intermodal railcars themselves being switched between trains (Rickett 2013). This cycling of intermodal railcars between terminals results in the railcar cost being similar to unit train service. Since there are likely multiple train departures from the same intermodal facility each day, locomotives shift from one train to another similar to manifest operations.

Due to the higher priority of intermodal freight and its suitability for highway transport, there is a possibility of mode shift to trucks as delays increase. The mode shift can be estimated using a freight mode choice model. The model developed by Hwang and Ouyang (2013) is based on the value of the shipment, truck travel distance, and the price of oil, with different model coefficients for each of ten freight classifications (Equations 3.10 and 3.11). Since this formulation does not explicitly consider transportation delays, the distance traveled by truck was reduced proportionally to reflect the additional time required to transport the delayed freight by train (Equation 3.12). Due to the difficulty in gathering mode shift data, default values are included here based on published sources. If proprietary data or models are available for specific circumstances, they can be applied instead.

$$P_n(t) = \exp(Un(t))/(\exp(U_n(t)) + 1) \quad 3.10$$

$$U_n(t) = a_n + b_nC_V + c_nL_R'C_{Oil} \quad 3.11$$

$$L_R'(t) = L_R^2/(L_R + V\times t) \quad 3.12$$

Where:

$P_n(t)$ – proportion of freight of a particular type being transported by truck
a_n,b_n,c_n – variables used in the utility calculation
C_V – value of goods shipped in an intermodal container ($/ton)
L_R' – adjusted route length to consider train delay (miles)
C_{Oil} – cost of crude oil ($/barrel)
Other variables as defined above

The above equations can be combined with the pertinent parts of Equations 3.3 and 3.6 to obtain the intermodal cycle cost (Equation 3.13).

$$\begin{aligned} C_P = {} & Q_T(Q_C(\lceil T_T,T_{PT}\rceil C_C + Q_IC_G(P_n(0) - P(T_D))/(P_n(0))) \\ & + T_T\ (Q_L(C_O+C_F)+C_W) \\ & + Q_LC_L(T_T + 2(T_{PL}(\lceil(T_D - T_{AL})/T_{PL}\rceil + 1 - P_L(T_L')) - \\ & T_D))) \end{aligned} \quad 3.13$$

Where:

Q_I – Average intermodal containers or trailers per car
Other variables as defined above

3.3 Application and discussion

To demonstrate how train delay costs vary, the equations developed in the previous section were applied to operating scenarios using representative input values. The following sections summarize the inputs used in the analysis and describe the resulting train delay costs.

3.3.1 Input parameters

The relationships between train delay and operating costs developed in Section 3.2 include several input parameters that describe baseline hourly costs common to all types of trains. This section will detail values for some of the input parameters that were developed from public data. Where applicable, additional details on calculating the parameters are provided in Appendix A.

3.3.1.1 Crew costs

Train crews are often paid through a combination of time and mileage rates with a certain minimum for each trip or shift. In the absence of knowledge about the compensation details for specific operating agreements on a route, an average hourly crew cost provides a reasonable estimate for the extra crew working time when trains are delayed. In 2015, North American Class 1 train crews made an average wage of $34.38 including straight and overtime, as well as other compensation (Surface Transportation Board 2016a). As North American freight trains typically operate with two crewmembers, the average crew cost would be $68.76. This approach considers the total average cost of an employee per hour, including benefits to consider the case where delays would require additional employees. This value can be adjusted if the wage rate is known for a specific route.

3.3.1.2 Locomotive costs

Train delay increases the amount of time a locomotive spends moving a particular train. As train delay increases, railroads must own more locomotives to move a given number of trains during a set period. Locomotive ownership costs vary depending on their particular attributes and if they were purchased or leased. Most modern mainline diesel-electric locomotives in long-distance freight service were purchased for between $1 and 2 million depending on the model and the options selected (Murray 2008). As of 2015, the cost of a newly-manufactured line-haul freight locomotive with the additional equipment and systems required to meet current emissions standards is approximately $3 million per unit (Black & Clough 2014).

For seasonal fluctuations in traffic demand, locomotives may be leased on a short-term basis during specific periods when additional power is needed. Locomotive lease rates range from under $100 to over $500 per day depending on the model and condition (Kruglinski 2008). Since only one-fifth of locomotives in the United States are leased (Association of American Railroads 2015a) and the lease rates are highly variable, this analysis derives the hourly locomotive ownership cost from its purchase price. The discounted annual purchase cost was determined from the reported $1.93 million purchase price of one common mainline locomotive (Murray 2008), a discount rate of 10.65% (Surface Transportation Board 2016b), assumed $200,000 salvage value, and a 25-year economic life (Dingler 2010). The resulting locomotive ownership cost is $25.71 per locomotive-hour. There is also a cost to operate the locomotive, including maintenance, inspections, and depreciation. In the absence of explicit operating costs, the average expense per hour was estimated as $61.38 (Association of American Railroads 2015a).

3.3.1.3 Fuel costs

Since 1981, all line-haul freight rail operations on the major North American railroads have been powered by diesel-electric locomotives (Marchinchin 2013; Association of American Railroads 2015b). The amount of fuel used by diesel-electric locomotives to move freight varies greatly according to the type of locomotive, train handling, speed, route topography, and operating conditions. For this analysis, the fuel consumption rate was estimated using the average duty-cycle throttle notch occupancy for mainline freight operations (U. S. Environmental Protection Agency 1998) and the throttle-notch specific fuel consumption of a 4,000-horsepower SD70 locomotive (Frey & Graver 2012). Using the calculated average fuel consumption rate of 58.79 gallons per hour (222 liters/hour) and an average diesel fuel price of $2.95 per gallon ($0.78 per liter) (Association of American Railroads 2015a), the average fuel cost is $173 per locomotive-hour. If actual train and route data are available, energy models or rail simulators may provide more accurate fuel use values for specific train delay conditions.

3.3.1.4 Railcar costs

Train delay increases the amount of time a railcar spends moving a particular freight shipment. As train delay increases, more railcars are needed to move a given number of shipments during a set period. To meet freight transportation demand, railroads use a combination of railcars owned by shippers, leasing companies, and railroads. When using railcars they do not own, including those owned by other railroads, a railroad must pay the owner of the car a fee called “car hire.” Car hire rates may have a time and distance component, but typically only the time-based rate is used (Buchanan 2009). If applicable, the additional distance cost can be calculated if a train is detoured onto a longer route. Some car hire rates are contractually agreed upon, while others are published as standard rates based on the railcar type, age, value, and amenities (R.E.R. Publishing Corporation 2007). For railcars that are owned by the railroad, the car hire rate equates to an opportunity cost associated with the railroad either not being able to use that railcar elsewhere or having to lease a railcar. For this analysis, it was assumed that the railcar costs are $0.58, $0.84, and $1.00 per railcar-hour for unit, manifest, and intermodal railcars respectively (R.E.R. Publishing Corporation 2007; Dingler 2010).

3.3.1.5 Revenue opportunity cost

Unless a shipper includes an on-time incentive or other late penalty in their contracts with the railroad, there is no explicit railroad cost for delayed freight. The railroad is subject to an opportunity cost of foregone demand (i.e. revenue) when train delays prevent movement of additional freight due to insufficient capacity or cause freight to shift to a competing carrier. If track capacity is not fully utilized, trains can be run with shorter headways to recover from delays (American Railway Engineering and Maintenance-of-Way Association 2012). If the delay is too large or the line is operating too close to its theoretical capacity, some trains may need to be canceled in order to maintain traffic flow, potentially resulting in lost revenue. As railway lines carry different types and amounts of freight, the revenue opportunity cost will be different for each line, but average values can be used for illustration.

To determine revenue opportunity costs, the average carload revenue is needed. It was assumed that all freight, outside of the “All Other” category are shipped in manifest service. That category includes apparel and textiles, empty semi-trailers, and miscellaneous mixed shipments and is primarily shipped via intermodal (Association of American Railroads 2015a, 2015b). Since unit and intermodal trains are in captive service, it was assumed that their ability to fulfill demand was not affected by train delay. This results in an average manifest train revenue of \$3,212 per car. Assuming an availability ratio of 0.75 (Dingler 2010), a cycle time of 26.88 days (Kwon et al. 1995), and an empty return ratio of 1.91 (Association of American Railroads 2015a), the lost revenue will be \$3.91 per railcar-hour. While the lost revenue cost may seem small, it will be accumulated over the entire train and delay time. If actual average lading values and rates are known, they can be used to more precisely determine lost revenue and mode shift.

The mode shift calculations require the per-ton value of the freight being shipped in addition to the direct revenue that will be lost. Due to the limited number of car types in intermodal service, the revenues could be calculated more explicitly and came to \$950 per car (Surface Transportation Board 2015). An intermodal car is defined here as a single well that can carry up to two intermodal containers (Dingler 2010), but in practice, a car can consist of multiple wells.

The lost revenue cost for intermodal was calculated for comparison and came to $8.94 per container-hour. To apply the mode shift model, a freight category must be assumed. For this analysis, intermodal shipments are assumed to be "Furniture, mixed freight, and miscellaneous manufactured product" (Hwang & Ouyang 2013), although a variety of goods are shipped via intermodal containers (Association of American Railroads 2015b; Surface Transportation Board 2015). The average freight value for these categories is $4,710 per ton (Center for Transportation Analysis 2017).

3.3.2 Unit train delay cost

Since unit trains are in captive service, the route length and baseline cycle time will directly affect the delay cost. Equations 3.1 – 3.3 were applied to 500-, 1,000-, and 1,500-mile (805-, 1,609-, and 2,414-km) routes using the values given in Section 3.1 and representative operating parameters (Table 3.1) to produce average unit train delay costs over a range of train delay amounts (Figure 3.1). As train delay increases, additional trainsets are required to maintain service frequency, causing a sudden increase in operating costs. This is reflected by the increase in average delay cost in Figure 3.1. Since each route length starts out with different buffer times between the cycle time and train departure interval, the amount of delay that must be accumulated before a new trainset is required is not constant. The 1,000-mile (1,609-km) route

Table 3.1: Assumed unit train values

Parameter (Variable)	Value
Operating speed (V)	25 mph[1]
Locomotives (Q_L)	2
Railcars (Q_C)	99[2]
Terminal processing time (T_A)	6 hours
Departure interval (T_{PT})	24 hours

1. 1 mile = 1.6 km
2. (Cambridge Systematics 2007; Dingler 2010)

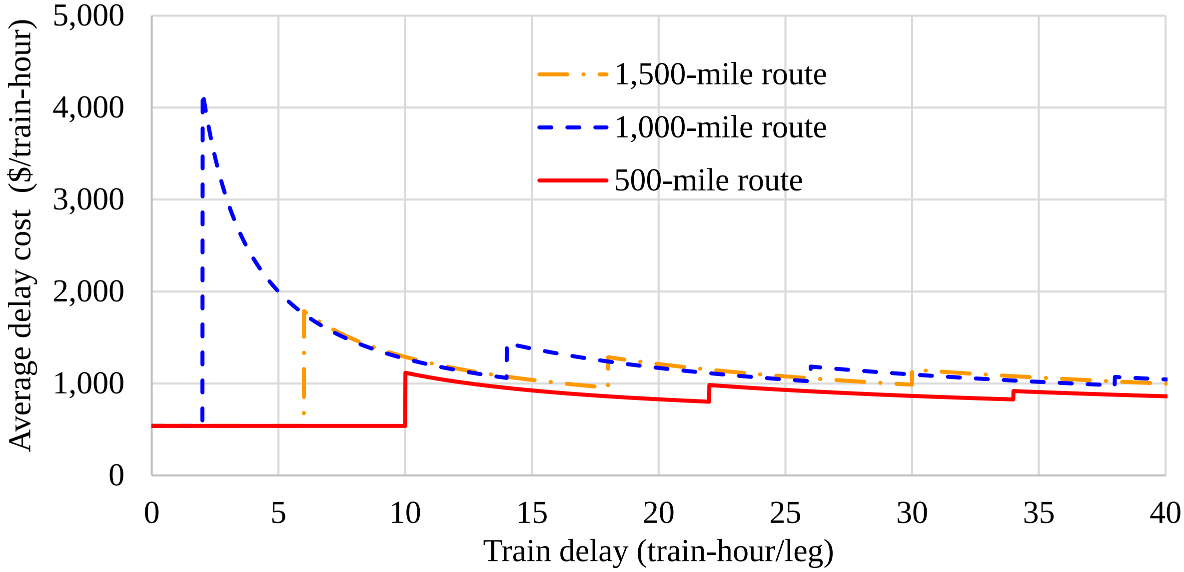

Figure 3.1: Average unit train delay costs

requires a new trainset after only two hours of delay, so the delay cost per train-hour is relatively high. The magnitude of the increase declines as the delay and number of trainsets in service rises because the costs are being averaged over longer delay and more trainsets.

For moderate levels of delay, trainset ownership during buffer times causes the average unit train delay cost to fluctuate in the range of $500 to $1,500 per train-hour but appears to be converging around $1,000 per train-hour. This is much higher than the isolated delay cost of $670 per train-hour. The discrepancy is likely due to the lumpy trainset costs that make up approximately 46-percent of the average cost.

3.3.3 Manifest train delay cost

Since manifest trains run largely independent of each other, the length of the route will not directly affect the hourly delay costs, although longer routes may have a higher likelihood of accumulating delay. Yard operations will have an impact since they affect how much buffer time is available to recover from delays. Equations 3.4 – 3.9 were used with the values in Section 3.3.1 and representative manifest train operating parameters (Table 3.2) to calculate average manifest shipment delay over a range of train delay amounts (Figure 3.2). The figure shows that the average amount of actual delay experienced by a shipment increases according to the PMAKE function for each departure. After the rolling stock has no chance of making the planned connection, no delay is accumulated until the probability of making the next train departure decreases below one, meaning all the additional buffer time has been consumed. Comparing the railcar and locomotive delay shows that as eligible departure frequency increases, the delay curve approaches a straight line.

Table 3.2: Assumed manifest train values

Parameter (Variable)	Value
Planned locomotive availability (T_{AL})	6 hours
Locomotives (Q_L)	3
Railcars (Q_C)	81 railcars[1]
Planned railcar availability (T_{AC})	12 hours
Loco. departure interval (T_{PL})	2 hours
Block departure interval (T_{PC})	24 hours
Railcar cutoff (T_{CC})	2 hours
Railcar max time (T_{CM})	12 hours
Locomotive cutoff(T_{LC})	2 hours
Locomotive max time (T_{LM})	6 hours

1. (Cambridge Systematics 2007)

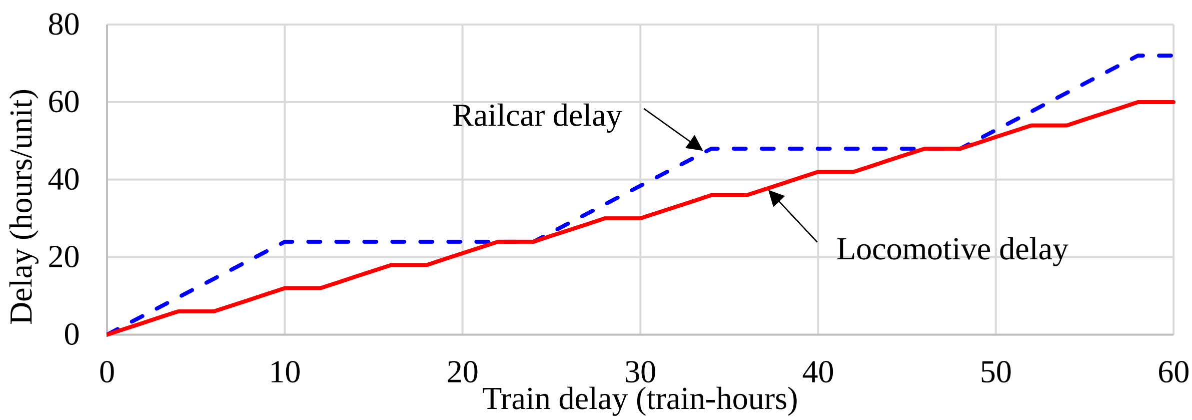

Figure 3.2: Average manifest delay accumulation

Since demand limitations will affect lost revenues, the average manifest train delay cost was plotted using G_C' of zero and the calculated value of \$3.92 per car-hour (Figure 3.3). The inclusion of the lost revenue costs makes the delay cost much more sensitive to railcar delay, and the two lines converge to approximately \$1,300 per train-hour with lading and \$950 per train-hour without lading. These values are slightly higher than the respective \$1,255 and \$938 per train-hour isolated delay costs. In this case, the yard initially amplifies delay costs since the yard schedule does not provide any initial buffer before the maximum guaranteed connection time. After all the railcars have missed their connections, the extra time before the next departure acts as a buffer mitigating delay. As more yards are added to a railcar trip, there will be increased uncertainty as to when the railcar will arrive at subsequent yards, potentially increasing the effect of a single hour of delay at the beginning of the trip. These observations can be used by planners to ensure sufficient yard dwell is built into the system for high priority cars or those that are frequently delayed.

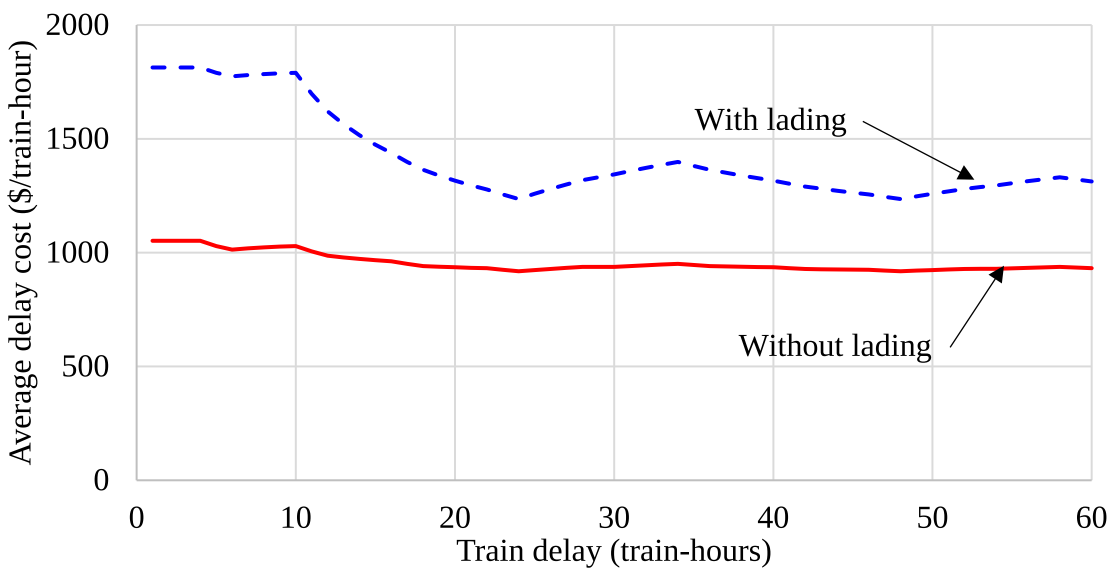

Figure 3.3: Average manifest delay cost

3.3.4 Intermodal train delay cost

As with unit trains, the cyclical nature of intermodal operations means that route length will affect how many railcars are required. Route lengths of 500, 1,000, and 1,500 miles (805, 1,609, and 2,414 km) were used with Equations 3.10 – 3.13, the values in Section 3.1, and representative intermodal train operating parameters (Table 3.3) to calculate average intermodal train delay costs for a range of train delay (Figure 3.4).

Table 3.3: Assumed intermodal train values

Parameter (Variable)	Value
Operating speed (V)	60 mph (97 km/h)
Locomotives (Q_L)	4
Railcars (Q_C)	77[1]
Average containers per car (Q_I)	1.8[1]
Total loading and unloading time (T_A)	8 hours[2]
Train Departure interval (T_{PT})	24 hours
Loco. departure interval (T_{PL})	2 hours
Planned loco. availability (T_{AL})	6 hours
Locomotive cutoff (T_{LC})	2 hours
Locomotive max time (T_{LM})	6 hours

1. (Cambridge Systematics 2007; Association of American Railroads 2015b)
2. (Rickett 2013)

Similar to the unit train average delay costs, the additional rolling stock costs are incurred at different times for different route lengths. Although the locomotive yard impacts are present, they are not noticeable in Figure 3.4 due to the frequency of train departures. The effect of mode shift can be seen in the initial part of the curves in Figure 3.4 between a delay of zero and the point where the first additional set of railcars are needed. Figure 3.1 shows that unit trains have a constant hourly delay cost until the first trainset is added. For intermodal operations, mode shift effects will begin occurring with the first instance of delay and are not linear (Figure 3.5).

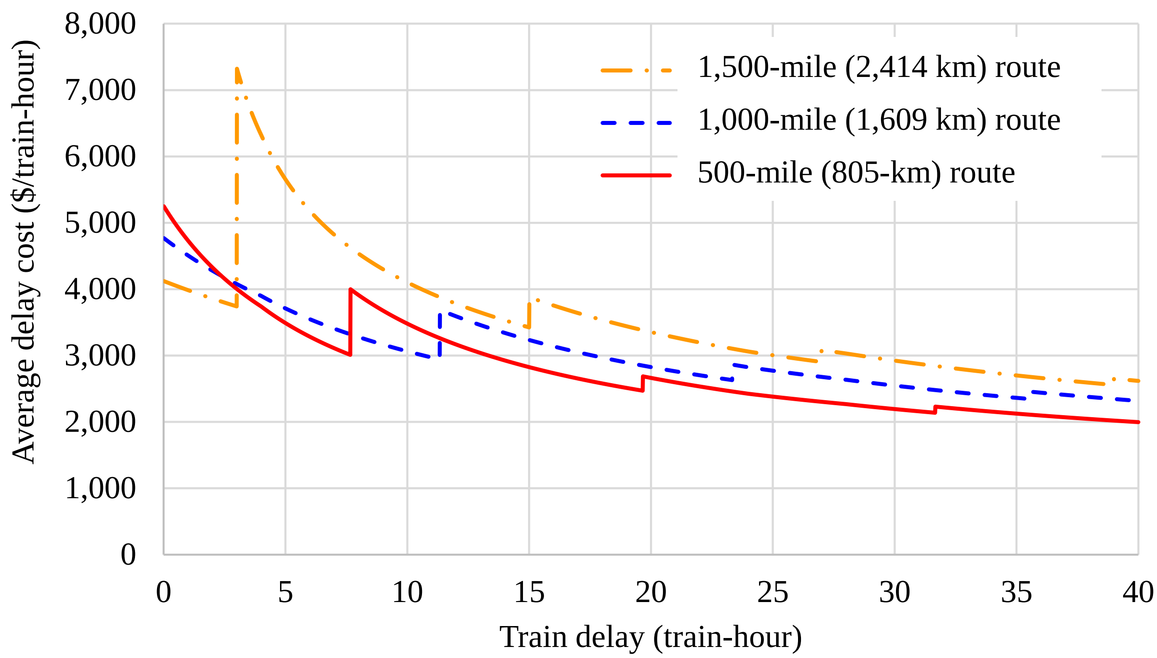

Figure 3.4: Average intermodal delay cost

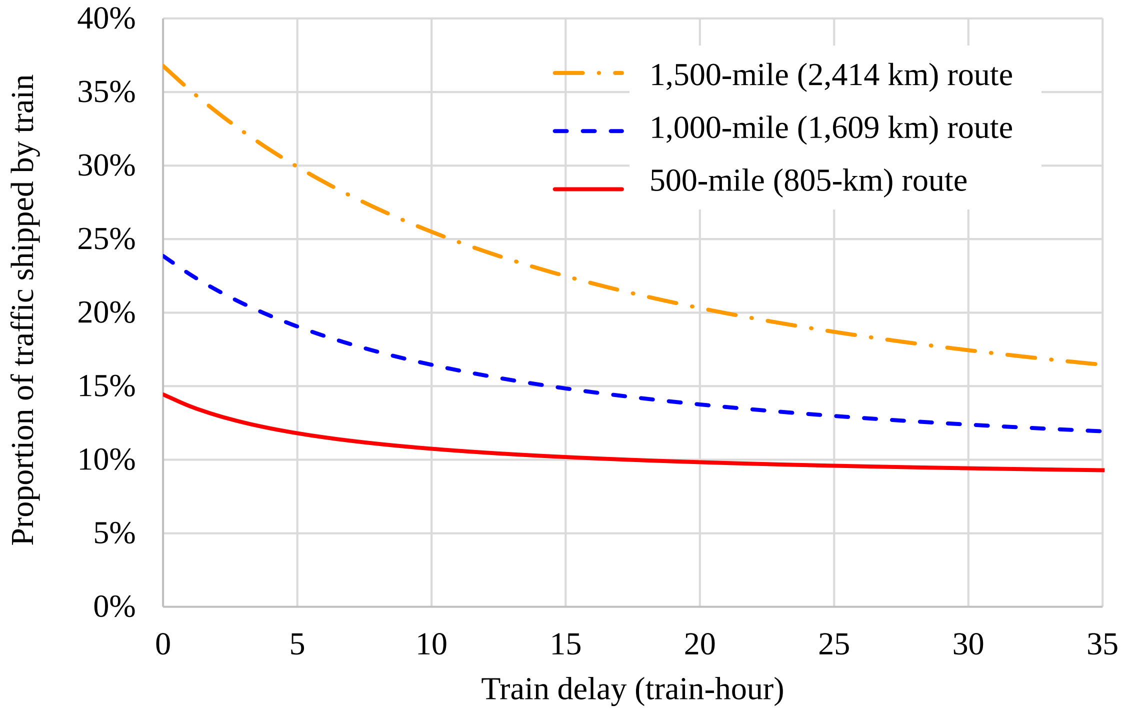

Figure 3.5: Intermodal mode shift effects

In general, mode shift becomes less sensitive to train delay as delay increases. This may be due to the way the adjusted truck shipping distance, L_R', was formulated, but it could also be because each hour of delay is a smaller proportion of the total travel time, reducing the impact of each additional hour. The mode shift costs also impact the convergence value for the average intermodal train delay cost because the initial proportion of freight traveling by rail is different for each route length, resulting in different average intermodal train delay costs per hour. The average intermodal train delay costs per train-hour converge between approximately $2,000 and $3,000 per train-hour but are higher for more moderate levels of delay. Using the lost lading cost as a proxy for mode shift, the $2,436 isolated train-hour cost is within the calculated range. In this case, mode shift opportunity costs are typically no more than a third of the total delay costs, but further analysis may be needed to ensure that it is not over represented.

3.4 Conclusions and future work

The type and length of train operations can have a large effect on how hourly train delay costs are accumulated. The methodology and equations described here can help in determining the added cost of delay for a particular train operation. Although crew, locomotive operation, and fuel costs are accrued at rates proportional to train delay, the cost of rolling stock is affected by operations at the terminals. The amount of buffer at the origin and destination terminals directly affects how much delay can be absorbed before additional unit train and intermodal rolling stock are required. Yard operational efficiency and planned yard availability will determine the extent that a yard acts as either a delay buffer or multiplier for manifest trains and intermodal locomotives. Intermodal trains also have the complexity of mode shift that introduces additional non-linearity to the train delay cost calculation. These complicating factors combine to show that for long-term changes in travel times, a single train delay cost is insufficient to describe what is happening in the entire operation. If planners do not consider the entire cost of train operations when determining the train delay costs, they risk underestimating the operational impacts of changes that affect train runtimes. Planners can also use the location of discontinuities in the intermodal and unit train delay cost curves to identify if there are rolling stock savings that might come from relatively small investments to reduce train delay.

Since the railroads are not the only stakeholders affected by train delay, an extension of this work is to identify the train delay costs accrued by other stakeholders, namely shippers and the public. Shipper and public costs associated with delayed trains are typically externalities, and therefore do not directly affect railroad costs; however, understanding these costs can assist the railroads in getting public and shipper support and assistance for projects that will reduce train delay. This is an area where additional research is warranted to improve modeling and understanding of comprehensive effects of train delay.

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CHAPTER 4.

COST AND DELAY OF RAILROAD TIMBER AND CONCRETE CROSSTIE MAINTENANCE AND REPLACEMENT[1]

4.1 Introduction

North American railroads spend billions of dollars each year on track maintenance, and crossties are one of the largest expenditures (Surface Transportation Board 2014). Therefore, crosstie investments should be made based on sound economics and maintenance performed in the most cost-effective manner. Track maintenance strategies differ in how frequently various components are renewed. In all cases, there are wide ranges of associated costs that vary based on operating conditions and affect which alternative is the most cost effective.

In order to accurately assess the cost-effectiveness of a maintenance procedure, the initial direct cost of labor and materials cannot be considered in isolation. Previous research has discussed life-cycle costing (LCC) for track maintenance and construction (Zarembski & Gauntt 1997; Zoeteman & Esveld 1999; Zoeteman 2001; Andrade 2008; Patra et al. 2009), but initial and recurring direct costs of labor and materials are not the only costs that should be considered. In an operating railroad environment, it is difficult to perform all required maintenance without at least some delay of trains. Transportation and engineering departments are frequently competing for track time. Delay costs due to track maintenance may be incurred by trains using the line undergoing maintenance, but may also affect other parts of the network. Traffic density on North American railroads is expected to increase, further exacerbating the delay associated

[1] This chapter is modified from Lovett, A.H., C.T. Dick, C.J. Ruppert Jr. and C.P.L. Barkan. 2015. Cost and delay of railroad timber and concrete crosstie maintenance and replacement. Transportation Research Record: Journal of the Transportation Research Board. 2476: 37-44. DOI: http://dx.doi.org/10.3141/2476-06. It is being reproduced with permission of the Transportation Research Board and does not imply endorsement by TRB of any product, method, practice, or policy.

with maintenance (Cambridge Systematics 2007). If the overall impacts and costs of maintenance-caused train delay are not fully accounted for, suboptimal decisions regarding infrastructure investment and maintenance strategies may result. Specific to the comparison of concrete and timber crossties, a frequently cited economic analysis of North American crossties states that its methods do not adequately account for the maintenance differences between the two types (Railway Tie Association 2006a; Zarembski & Kondapalli 2007). Therefore, a new method is needed to understand the economic comparison between these two crossties types.

4.2 Life-cycle costs

Life-cycle cost analysis is best applied in situations where the asset has substantial upkeep costs and must consider not just the costs directly related to the component in question, but also any costs affected by the component selection (Brown & Yanuck 1985). The methodology set forth in this research considers four main cost categories: renewal, accident, slow order, and other track maintenance. Each of these categories can be further divided into direct, delay, and network costs. Previous research on track maintenance has considered direct costs and some have included delay costs in their LCC analyses, but none appear to have factored in network effects or additional delay during the time for normal service levels to resume after the track has reopened (Zarembski & Gauntt 1997; Simson et al. 2000; Patra et al. 2009). Understanding network effects and delay beyond just those trains interrupted by the track outage is important because they can have a significant effect on the indirect costs of track maintenance.

Two parameters essential to LCC analysis are the discount rate and the analysis time period. The applicable discount rate for an LCC analysis will vary between owning entities and is largely based on the cost of capital. Proper selection of the discount rate can have a substantial impact on the results of LCC and other present-value cost analysis techniques. Higher discount rates will favor alternatives with comparatively low initial costs and higher operating costs, such as timber crosstie track, while lower discount rates will favor the opposite conditions, such as track constructed with concrete crossties (Dimson 1989; Brealey et al. 2007).

The time period considered by an LCC analysis is based on the lifetime of the components in question (Brown & Yanuck 1985; Flanagan et al. 1989). For crossties, this is somewhat ambiguous as timber-crosstie track does not have a finite lifetime per se. Failed crossties are renewed as needed at a rate that will vary based on operating conditions, such as climate and traffic levels, and renewal threshold (Wells 1982). A commonly used approach to determine the distribution of failed timber-crosstie ages is the Forest Service Products Curve (FSPC) (MacLean 1957; Wells 1982; Railway Tie Association 2006b). Previous research has shown that crosstie replacements are most efficient when over 800 are replaced per mile at a time (Elkaim et al. 1983). Therefore, I developed a model using the FSPC to predict years when a track is expected to have over 800 failed crossties per mile as an aid to determining when and how many need to be replaced. This model was used to determine when renewals will take place on a track with 20” (508 mm) crosstie spacing and an average life of approximately 30 years. This analysis shows that renewals occur every 9 to 10 years when between 800 and 900 crossties per mile have failed (Figure 4.1). For analysis purposes, the renewal rate was set as a 850 timber-crosstie-per-mile renewal every nine years. In practice, railroads can use historical maintenance data to develop average crosstie renewal rates for specific track segments as the average life will vary based on operating conditions and environmental factors.

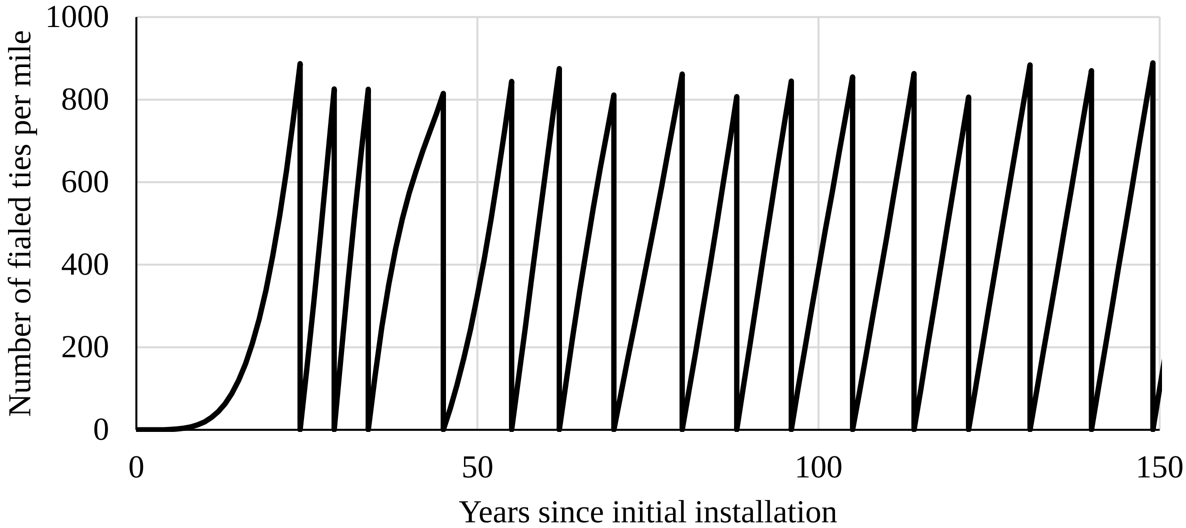

Figure 4.1: Failed timber crosstie replacement pattern for 20" spacing and 30-year life

Concrete crossties are typically modeled as being renewed out-of-face, i.e. every crosstie is replaced at the end of their estimated 40- to 50-year service life (Zarembski et al. 2004; Zarembski & Patel 2010; Railway Tie Association 2012; Cloutier 2014). This is more like a typical component replacement and makes for a simpler LCC analysis. Concrete crosstie life was taken as 45 years, as this was an average value and resulted in it being a multiple of the timber-crosstie renewal cycle. This also results in LCC time horizon finishing the year before a renewal for both alternatives. It should be noted that concrete crossties have not been in service in North American heavy haul applications long enough to satisfactorily estimate if the exact circumstances when the end of life cycle replacements will take place and what the costs of replacement will be.

4.2.1 Direct costs

4.2.1.1 Renewal costs

Direct renewal costs (i.e. labor and materials) can be determined in several ways. One method uses unit equipment, labor, and crosstie costs (Elkaim et al. 1983), and would be reasonable for a railroad or other entity with access to current values. This method's results would be questionable if historical costs were simply updated to current dollars without knowing how relationships between the parameters have changed with the development of new maintenance techniques and equipment. Another method is to use published industry values of installation costs. The Railway Tie Association (RTA) uses $95 per timber crosstie and $200 per concrete crosstie installed, including all material and labor costs (Railway Tie Association 2006a). Although these values were used for analysis in this paper, some industry sources have said current concrete crosstie costs are much closer to those of timber crossties. The impact of varying costs will be examined in the sensitivity analysis. In the LCC, these values are multiplied by the number of crossties replaced during each renewal to determine the direct cost.

4.2.1.2 Accident Costs

Accidents are unscheduled events that can be modeled based on average frequency and consequence. The Federal Railroad Administration (FRA) maintains a database of rail accidents with damages above a monetary threshold (Federal Railroad Administration 2011), but this database includes limited information about the track structure at derailment locations. Thus to make comparisons between the accident rates and costs on concrete and timber-crosstie track, additional analysis using track structure data provided by a Class 1 railroad was conducted.

The railroad data indicated that 17% of track-caused accidents occurred on concrete-crosstie track. This rate needs to be normalized by ton-miles as not all track has the same annual tonnage, and industry professionals indicate that concrete crossties are typically used on track segments with more traffic. The length of concrete-crosstie track on the railroad was estimated by assuming 6.5% of all crossties are concrete (Railway Tie Association 2015) and a standard concrete crosstie spacing of 24 inches (609.6 mm). The railroad also provided the average annual tonnage for concrete and timber-crosstie track. This resulted in a concrete-crosstie track accident rate of 0.152 per billion-ton-miles (0.104 per billion-Mg-km) and a timber-crosstie track accident rate of 0.208 per billion-ton-miles (0.142 per billion-Mg-km). This is not to imply a causal relationship with crosstie type. Accident rates vary based on a number of factors, including track class, annual tonnage, and other operating characteristics (Liu et al. 2017), that were not accounted for in this preliminary analysis. Concrete crossties are generally used in track with higher tonnage and FRA track class. Both of these factors are correlated with a lower accident rate (Liu et al. 2017). In contrast, timber crossties are widely used in track with a variety of FRA track classes and annual tonnage. These relationships make it difficult to determine how much of the accident rate variability comes from the crosstie type. Additional railroad data will enable development of accident rates for track with each type of crosstie and track class combination that are better aligned with specific operating conditions than the preliminary values presented above. In the absence of these detailed rates, the preliminary values are used here simply to illustrate the analysis process.

The cost of an accident is also likely to differ between the two crosstie types. Based on the FRA database for 2011-2013 and the location of concrete crossties, the average cost of a track-caused accident was $363,811 for accidents on concrete- and $218,850 for timber-crosstie track (Federal Railroad Administration 2014a). Accident costs on concrete crosstie track may be higher because they typically need to be replaced after each derailment, whereas timber crossties are more resilient. Indirect costs such as delay or network effects are not accounted for in the FRA data, so these must be taken into consideration in specific scenarios.

4.2.1.3 Slow Order Costs

Like accidents, slow order costs are modeled based on their frequency and cost. For each track class, the FRA Track Safety Standards specify the required number of good crossties for tangent and curved track (Federal Railroad Administration 2014b). Tracks that do not meet these criteria are subject to slow orders where train-operating speed is reduced until maintenance is performed. The expected number of slow orders caused by crosstie degradation can be calculated in a method similar to the Poisson process using a Weibull approximation of the FSPC and average replacement rate (Equations 4.1 and 4.2). The Weibull distribution was selected because it has previously been used in other crosstie life studies (Lake et al. 2000) and fits the data better than other models. Further discussion on this model can be found in Appendix B.

$$P_{39} = \begin{cases} 1 - \sum_{\sum i_j = 0}^{f} \prod_{j=1}^{k} \binom{n_j}{i_j} p_j^{i_j} \left(1 - p_j\right)^{n_j - i_j}, & n_j \geq i_j \forall\, j \\ 0, & else \end{cases} \tag{4.1}$$

$$p_j = 1 - \exp\left[-\left(\frac{y + (j-1)c}{\beta A}\right)^{\alpha}\right], \qquad y + (j-1)c > 0 \tag{4.2}$$

Where:

- P_{39} – probability of a slow order in an average 39-foot track segment
- f – maximum allowable number of failed crossties
- k – number of age groups
- n_j – number of crossties in age group j
- i_j – number of failed crossties in age group j
- p_j – failure probability of a crosstie in age group j
- y – years since the last crosstie renewal
- c – years between crosstie renewals
- A – average crosstie life
- α,β – Weibull shape parameters corresponding to the FSPC

The calculated probability represents the average number of slow orders per 39 feet of track during a given year and can be multiplied by the number of track miles to find the expected number of slow orders per year. This rate is calculated on an annual basis since the probability will change as the crossties age and will reset after each renewal. I assumed that once a slow order is repaired, the presence of newer crossties will reduce the expected number of slow orders in subsequent years. Individual railroads have their own operating protocols that may impose slow orders under other crosstie failure conditions (e.g. clusters) (BNSF Railway Company 2000; National Railroad Passenger Corporation 2013) and will affect this probability calculation. This methodology can be adapted to specific operating protocols, but as the FRA standards are applicable to all railroads, they were used for this analysis.

The direct costs for each slow order consist of the labor and material cost of replacing sufficient crossties to meet the FRA standards. For this analysis, it is assumed that two crossties are replaced for each slow order. The cost of replacing the two crossties is multiplied by the expected number of slow orders per year to calculate the annual direct slow order cost.

4.2.1.4 Other Track Maintenance Costs

Other track maintenance related to crosstie condition was assumed to consist of rail maintenance and tamping. Previous research has shown that timber crosstie quality has an insignificant impact on rail maintenance (Elkaim et al. 1983), but concrete crosstie manufacturers claim that concrete crossties improve rail life (Koppers 2014; Rocla Concrete Tie Inc 2014). Since no independent data were available that support this claim, it was not considered in this analysis. Improved crosstie quality has been shown to result in reduced surfacing costs (Elkaim et al. 1983), though this finding was based on timber crossties. I assumed that concrete crossties would equate to good crosstie conditions and therefore have lower surfacing costs. Discussion with railroad personnel and concrete crosstie manufacturers suggests that concrete crossties hold line and surface better (Koppers 2014; Rocla Concrete Tie Inc 2014), so I also assumed that concrete-crosstie track would need to be surfaced less frequently. Specific maintenance costs and frequencies are given in subsequent sections.

4.2.2 Delay and Network Effects

Since the impact of train delay is not necessarily limited to the line that a service disruption takes place on, this chapter considers the costs of both primary and secondary delays. Primary delay is the delay directly associated with trains on the disrupted track, while secondary delay accounts for network effects that lead to delay costs associated with other trains on the network.

Primary delay is calculated as the increased travel time associated with a service disruption. The extra travel time may be due to trains being rerouted onto a longer line or delayed because the system has less flexibility due to a portion of the track being out of service. The increased travel time is applied to all trains that would be affected by the disruption. For track maintenance, this is likely a few hours a day over several weeks, but for unplanned disruptions, it could take 24 hours or more until the track is repaired. This is because unplanned disruptions do not allow for prior scheduling of rerouting.

To determine the increased travel time, several options are available including rail traffic simulation or parametric delay-volume curves. Simulation gives the ability to test specific track and traffic configurations, but new track layouts need to be developed for every track configuration. A railroad that is already using simulation software could reasonably use this method by drawing from their library of network simulation models. For general use in a wide range of situations without specialized software, a more analytical approach would be beneficial. Parametric models, such as the delay-volume curves are well-suited to this analysis (Sogin et al. 2013; Shih et al. 2014), and one developed by Sogin et al. (2013) was used here (Equation 4.3).

$$D = (S_1 - S_2 x)e^{kV} \tag{4.3}$$

Where:

- D – average train delay (min)
- S_1 – single-track delay (19.5206)
- S_2 – delay mitigation constant (19.149)
- x – double-track percentage
- k – congestion factor (0.0471)
- V – traffic volume (trains per day)

For maintenance performed on double-track lines, the percentage of double track will effectively decrease during the maintenance work window. For maintenance on single-track lines, traffic must be stopped during the work window. For all lines, traffic will stop during post-accident repair, assuming all tracks are removed from service after an accident. Closing all lines is a worst-case scenario, but repairs would likely be delayed because of safety concerns if adjacent lines were kept active. When the track is reopened following maintenance, a double-track section will eventually return to normal, but for single-track sections or after accidents, there will be some residual delay. For single-track sections, the traffic is assumed to clear before the next maintenance window. After accident clean up, it will take approximately two days for the traffic to return to normal after the disruption is cleared, assuming traffic normally operates at 65% of theoretical capacity. This value is slightly more conservative than the industry recommendations (American Railway Engineering and Maintenance-of-Way Association 2012). During this time, the track will be operating at its theoretical capacity to move as many trains as possible in an effort to minimize the length of the recovery time (See Chapter 5 for further discussion of this concept).

Network effects are more complex and can manifest in a variety of forms experienced by trains beyond those that typically run on the disrupted line. The most easily measured network effect is the delay experienced by traffic on other lines if trains have been rerouted around a disruption. Trains will only be rerouted if the alternate route results in less delay than continuing on the original route. If a system is large enough, rerouting may result in delay being propagated through many lines as alternate routes reach capacity and traffic is further rerouted. This network effect can be measured in the same manner as direct delay. Using a simulation tool will allow for the simultaneous calculation of both the direct and network delay.

Additional delay can also be experienced by railcars that miss their scheduled connection at intermediate yards. The cost of expected connection delay is a function of the distribution of train departure times from the yard and the value of the lading being shipped. Yards that are optimized to reduce the amount of time cars wait in the yard or to handle a large amount of high-value freight will have higher delay consequences because even small amounts of delay may result in a missed connection. Another form of network cost is having a train crew reach their Federal hours-of-service limit. In these instances, a replacement crew must be transported to where the train has stopped, and the old crew transported back. If the crew change was supposed to occur before the train moved to a new territory, the original replacement crew will also be delayed. For both conditions, specific circumstances are needed to evaluate these costs.

The cost of train delay per hour varies based on a variety of factors broken into five main categories: crew, cars, lading, locomotives, and fuel (Schafer 2008; Dingler et al. 2011) (See also Chapter 3). Most of these costs vary with train and commodity composition. Based on the analysis in Chapter 3, the isolated crew, car, lading, and locomotive costs are approximately $950 per train-hour, assuming an average manifest train composition and no yard effects. Fuel costs are the most variable as they depend on the type of delay imposed on a train and the number and type of locomotives in the consist. If delay results in a train being stopped, such as in a complete track outage, then the train is assumed to idle for the additional time. In the case of running delay, e.g. a train is rerouted to a longer route or is able to move on the line with additional delay because a siding or section of double track is being maintained, the locomotive is assumed to be operating according to the average locomotive duty cycle (U. S. Environmental Protection Agency 1998). Fuel cost is based on fuel consumption of a 4,300-horsepower mainline locomotive at an average fuel price (Association of American Railroads 2012; Frey & Graver 2012). This results in an idle and running delay cost of $1,009 and $1,505 respectively. These numbers can, and should, be adjusted to consider the actual train composition and costs on a given line. If a train energy model is available in the train simulator being used, the fuel cost can be calculated when delay is determined. These delay values agree with those in Chapter 3, so even though yard effects are not being explicitly considered in this analysis, the results appear reasonable.

Slow orders are a unique situation because trains continue moving over the track but must slow down for a specific segment. The model conservatively calculates the amount of additional time a train will take to slow to the reduced speed (assumed to be that of the next lower track class), traverse the slow-ordered track, and then accelerate back to normal track speed. The calculated time is applied to the expected number of slow orders over the line and priced at the running delay cost.

4.3 Sensitivity analysis

Some of the inputs required for this analysis may be difficult and expensive to gather for a large number of lines, so understanding which inputs have the largest impact on the LCC is important. Knowing the influence of each factor allows analysts to concentrate on gathering input data that are most significant. Inputs with lower impact can be approximated if they are not readily available (Lovett et al. 2013). Since situations with and without alternate routes involve substantially different considerations, the sensitivity analysis was performed for each case independently. A total of 39 different input factors were considered, covering virtually all track, operations, and disruption characteristics (Table 4.1).

For the scenario with an alternate route, the alternate route characteristics were varied with the same base and bounds as the primary route. When an alternate route is present, a reroute ratio, or the ratio of the length of the alternate route to the length of the main route, is also specified. Base route characteristics are based on Sogin et al. (2013) to match the operating conditions for Equation 4.3. Track possession, equipment set up times, crosstie renewal rates, tamping speeds and costs, and train weights are based on published values and industry averages and analyses (Elkaim et al. 1983; Burns 1987, 1989; Illinois Department of Transportation 2011; Association of American Railroads 2012). The upper bound was selected to be approximately double the base value, with the lower bound about 10 percent of the base value. Some categories, such as track class and crosstie spacing, already have specific limits that were used to define the lower and upper bounds. Accident costs can be an order of magnitude higher for lines with hazardous material traffic, so the upper bound was increased accordingly. The minimum amount of double track is limited by the siding length and spacing, while track possession time has to be long enough to allow work to be done. The timber crosstie renewal threshold was limited by the crosstie LCC model. Using a reasonable range of values allows for a more complete picture of how sensitive the outputs are to each of the inputs (Eschenbach 1992).

Table 4.1: Sensitivity analysis categories and values

Factor	Lower bound	Base value	Upper bound
Track characteristics			
Degrees of curvature	1	2	4
Track class	1	3	5
Timber crosstie spacing (inches[1])	18	20	24
Concrete crosstie spacing (inches[1])	18	24	30
Route length (miles[2])	25	240	500
Siding/crossover spacing (miles[2])	1	10	20
Percent double-track	0.19	0.5	1
Reroute ratio	1	2	5
Operating characteristics			
Trains per day	3	30	60
Average train weight (tons[3])	600	6,723	12,000
Delay costs less fuel ($/train-hour)	100	950	1,900
Running fuel cost ($/train-hour)	50	555	1,110
Idle fuel cost ($/train-hour)	5	59	100
Discount rate (%)	1	6	12
Disruption inputs			
Track possession time (hours)	2	6.5	12
Equipment set up and tear down time (hours)	0.25	0.5	1
Timber crosstie costs ($/crosstie)	10	95	200
Timber renewal threshold (crossties per mile[2])	600	800	1,000
Timber renewal speed (mph[2])	0.05	0.22	0.40
Timber average crosstie life (years)	3	30	60
Concrete crosstie costs ($/crosstie)	20	200	400
Concrete renewal cycle length (years)	30	45	55
Concrete renewal speed (mph[2])	0.05	0.16	0.3
Timber accident rate (accident /per BTM[4])	0.01	0.208	0.4
Timber accident costs ($/accident)	30,000	218,850	1,000,000
Concrete accident rate (accident /per BTM[4])	0.01	0.152	0.4
Concrete accident cost ($/accident)	30,000	363,811	1,000,000
Slow order application length (miles[2])	0.01	0.1	2
Slow order application time (hours)	0.5	5	10
Crossties replace to repair a slow order	1	2	5
Timber tamping speed (mph[2])	0.05	0.28	0.5
Timber tamping cost ($/mile[2])	600	18,031	35,000
Timber tamping frequency (years)	0.5	2	8
Concrete tamping speed (mph[2])	0.05	0.28	0.5
Concrete tamping cost ($/mile[2])	600	6,341	35,000
Concrete tamping frequency (years)	0.5	4	8

1. 1 inch = 25.4 mm
2. 1 mile = 1.61 km
3. 1 short ton = 0.907 Mg
4. 1 billion-ton-miles (BTM) = 1.46 billion-Mg-km

The arc elasticity method (Allen & Lerner 1934) was used to compare the relative influence of each factor on the ratio of the timber to concrete crosstie LCC (Figures 4.2 and 4.3). Elasticity measures how the output changes with respect to the inputs. If an input value is adjusted and the output changes in the same direction, then there is positive elasticity. Output changes that are opposite the input changes indicate negative elasticity. Arc elasticity uses percent change to normalize results and remove the impact of using different units (Allen & Lerner 1934; Lovett et al. 2013). Exact values for the sensitivity analysis are provided in Appendix C.

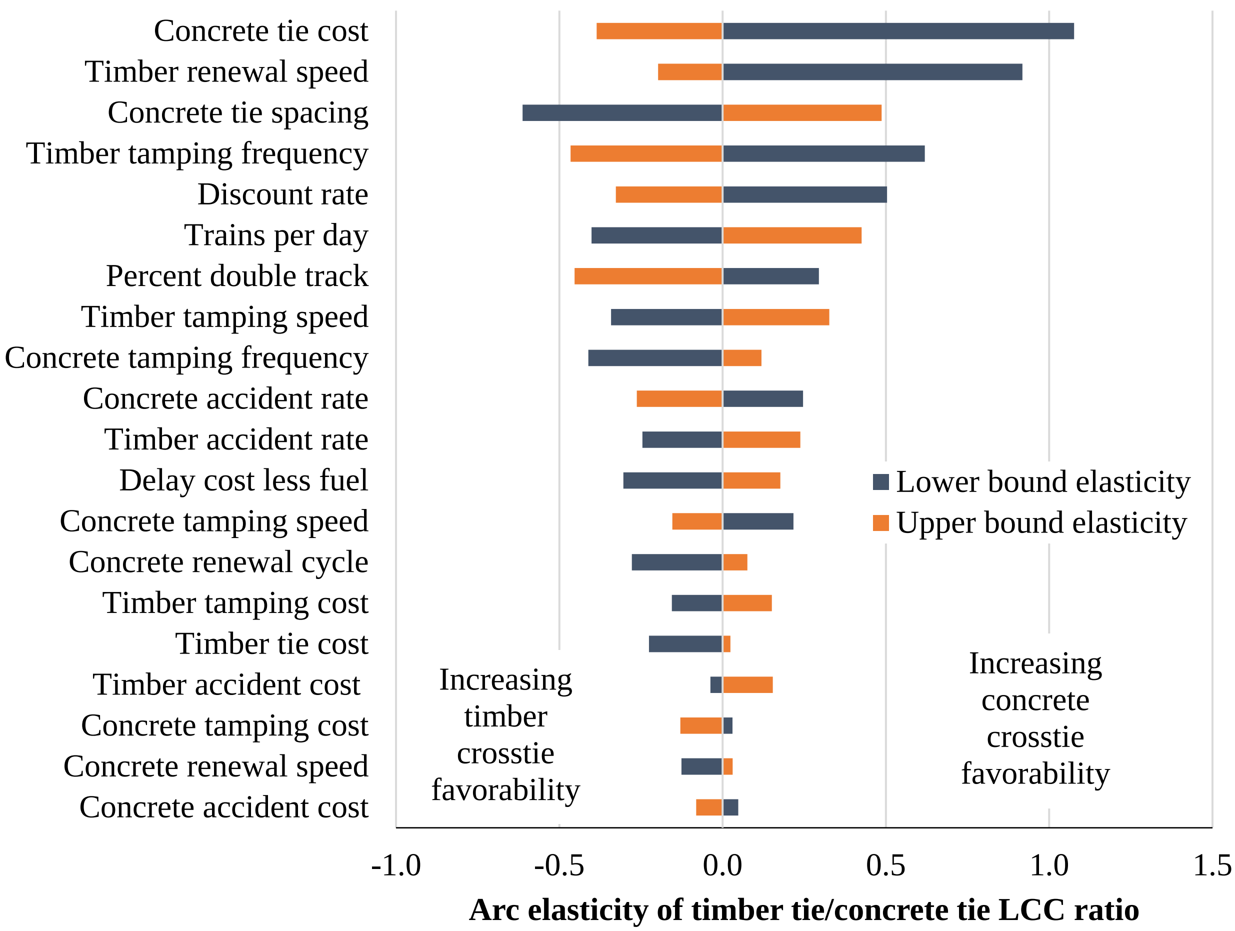

Figure 4.2: Sensitivity analysis results for the route without an alternate route

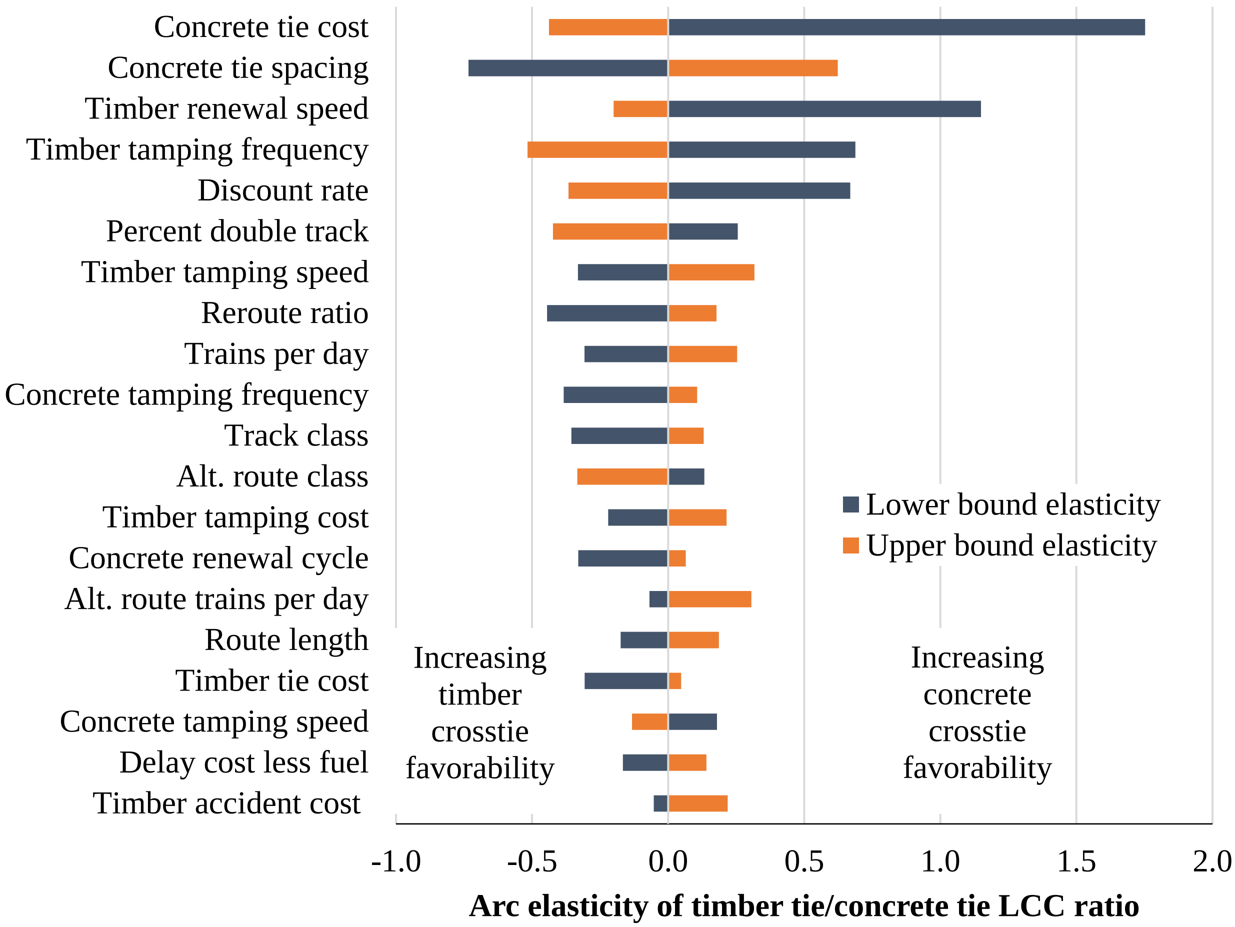

Figure 4.3: Sensitivity analysis results for the route with an alternate route

The two scenarios share 15 of the top 20 factors. The remaining factors for the alternate scenario pertain to the alternate route. This implies that when an alternate route is available, its favorability can have a substantial impact on the selected crosstie type. Among the factors that are shared between the two scenarios is the delay cost, excluding fuel. This indicates that fuel costs, which are more difficult to determine than some of the other delay cost components, do not need to be as precise. Many of the shared factors that affect direct costs (e.g. crosstie spacing or tamping frequency) also affect delay costs.

It was mentioned above that some in the industry think the concrete crosstie replacement cost value used by the RTA is too high. This analysis shows that even a relatively small change in the concrete crosstie cost will have a large impact on their favorability. This is likely because all concrete crosstie renewal costs are incurred in the first year and are not discounted, so care needs to be taken to ensure that these costs are accurately estimated. The high sensitivity of the discount rate will increase its impact for organizations with a high discount rate, further biasing the analysis toward timber crossties. Thus, organizations with different methods of computing the discount rate may come to different conclusions about preferred crosstie type even if all other factors are equal.

4.4 Case study

To show how the model handled various situations, a case study was conducted with a network of four lines (Figure 4.4). All lines are FRA Class 4 track with moderate curves and climate, matching the conditions used to develop the timber crosstie renewal cycle and 30-year

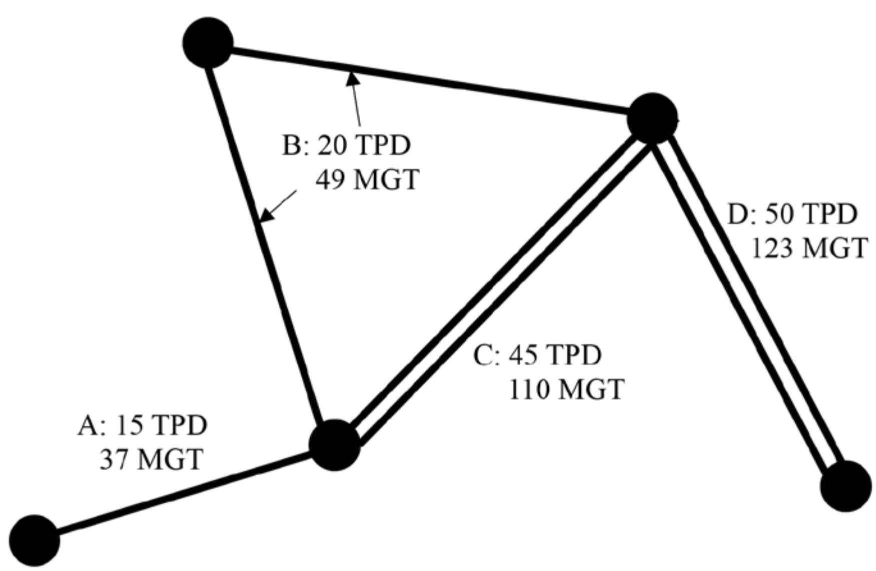

Figure 4.4: Case study network with segment traffic levels in trains per day (TPD) and million gross tons per year (MGT)

crosstie life assumption (Railway Tie Association 2006b). The timber-crosstie track is tamped every year. Single-track lines have 10-mile siding spacing and double-track lines have full double track. Except where other route-specific values are given, the remaining characteristics are the same as the base case in Table 4.1. I assumed that there are no additional hours-of-service crew or yard delay costs. Output values are provided in Appendix D.

By comparing the cost components for each route and crosstie alternative, the differences between each can be observed (Figure 4.5). On most of the routes, concrete crossties are more cost effective. For line B, timber-crosstie track may be more cost effective because there is an alternate route that can be used during maintenance and accident recovery. When part of line B is out of service, line C may be an attractive rerouting alternative because it has double track, while still allowing access to the customer at the midpoint of line B. On line C, the delay does not have as big an impact due to the second main track. One cost that appears to have virtually no impact

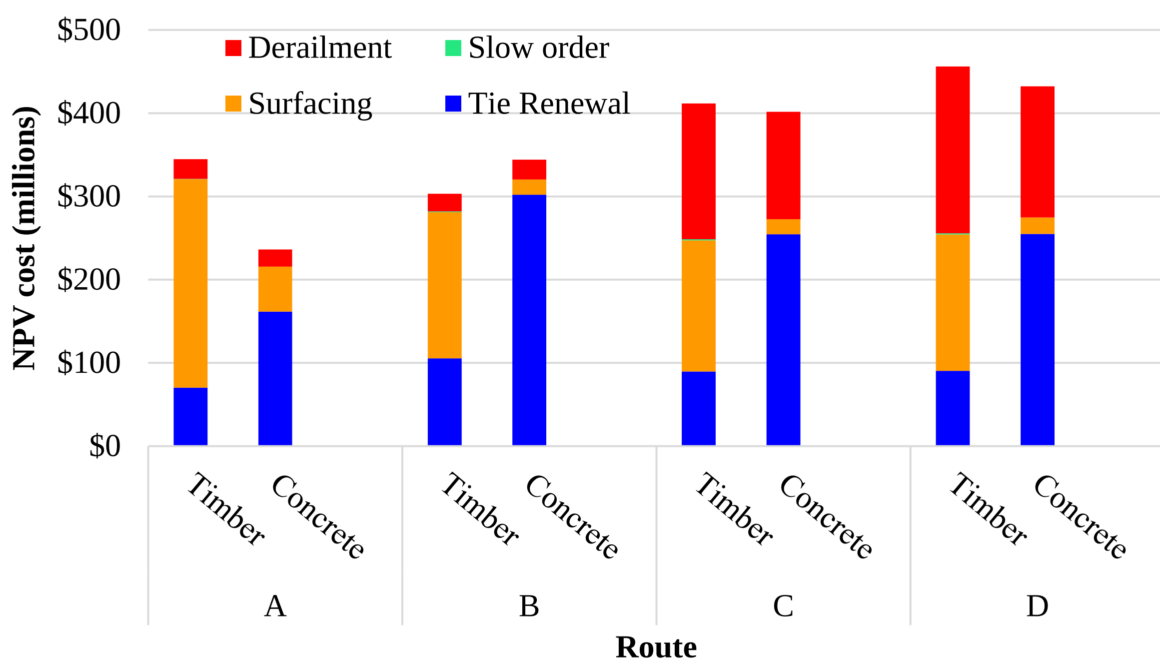

Figure 4.5: Case study results divided by cost category

is the cost of slow orders, as they were found to be orders of magnitude lower than the other cost categories. This is one of the most computationally intensive costs to calculate, so it may not be justified to calculate specific data for this category.

Accident costs are another category with unexpected results. While the increased accident cost for concrete crossties more than offsets their lower accident rate, the timber crossties still have higher derailment costs. This is due to delay, which is the same for both types but is incurred more frequently in the timber-crosstie scenario because of the higher accident rate.

Another perspective can be gained by separating the costs by type (Figure 4.6). While delay costs do not typically comprise the majority of the total cost, in all cases, neglecting delay and network costs results in concrete crossties being more expensive than timber. When delay is considered, concrete crossties become substantially more competitive and even the low-cost alternative. On line B, considering delay costs makes concrete crossties slightly more

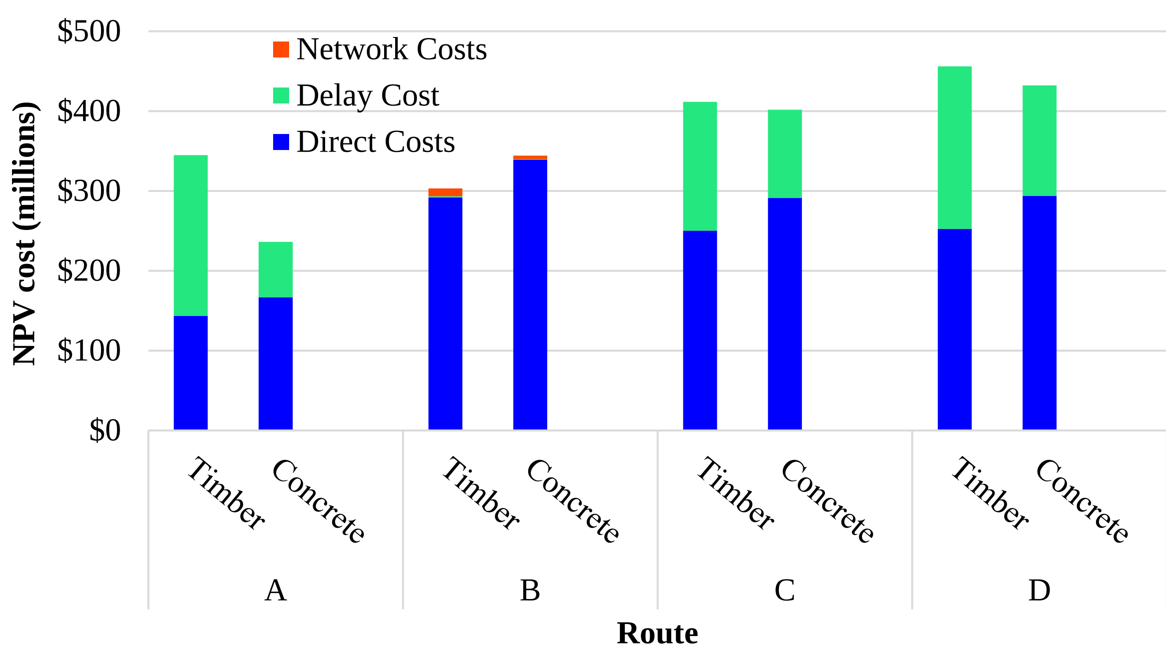

Figure 4.6: Case study results divided by cost type

competitive and if re-crew or yard delay costs were considered, the balance might be changed. Line B is the only one to experience network delays because rerouting is not cost effective for Line C. This can be a critical consideration when explaining to operating personnel why maintenance or upgrades need to be performed.

4.5 Conclusions

This analysis shows that considering delay and network costs can strongly influence maintenance decisions. Maintenance and infrastructure planners can use the results of the sensitivity analysis to identify where data-collection efforts should be concentrated to ensure the accuracy of the life-cycle cost analysis. The model's sensitivity to concrete crosstie cost indicates that if the RTA values are too high, then any analysis using them may suggest timber crossties are more favorable than they actually are. The sensitivity of the discount rate shows how organizations with different business objectives may draw different conclusions about what crosstie type is least expensive for a particular application.

The case study shows how delay and network effects can influence the comparison between timber and concrete ties, and that even if direct accident risk is higher for a particular alternative, the option with the higher accident rate may have higher overall costs due to the increased frequency of network disruptions.

4.6 Future work

The next steps for refining this model are to improve its applicability and validity. The model framework can be adjusted to compare any set of maintenance options. This allows for a wider range of comparisons on all aspects of the track. Additional work also needs to be done on gathering validation data and refining the component-specific accident rates. While much of the data used in this model is based on general industry data, a true validation will require data from actual railroad lines. This will allow the model to better represent the actual conditions of the railroad and be applicable to a wider range of scenarios.

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CHAPTER 5.

OPERATIONAL IMPACTS OF SLOW ORDERS ON RAIL LINES IN NORTH AMERICA [1]

5.1 Introduction

Temporary speed restrictions are a substantial concern for major North American railroads. Commonly referred to as “slow orders,” these restrictions are applied to a segment of track when it is deemed unsuitable for trains to operate at the normal posted maximum speed. The main operating problem associated with slow orders is a reduction in average train speed, which is a metric of network fluidity reported by all major railroads in the United States (Association of American Railroads 2016). As discussed in Chapter 3, decreasing average train speed increases railway-operating costs at the network level by increasing the required number of railcars, locomotives, and crews required to move a given amount of traffic. It is difficult to allocate these network cost increases to individual temporary speed restrictions and use these as the basis for track maintenance allocation decisions. The analysis in Chapter 4 indicated that slow orders do not have enough impact on railroad operations to materially influence such decisions. Since slow orders are a substantial concern for North American railroads, further study was needed before definitive conclusions regarding the operational impact of slow orders could be reached. Factors that may affect slow order risk include the rate of occurrence, slow order length and duration, the cost of train delay, and potential compounding effects on subsequent trains and adjacent lines. In considering these factors, this chapter attempts to improve upon previous research on the cost and operational impact of slow orders.

[1] This chapter is modified from Lovett, A.H., C.T. Dick and C.P.L. Barkan. 2017. Predicting the Cost and Operational Impacts of Slow Orders on Rail Lines in North America. In: *Proceedings of the International Association of Railway Operations Research (IAROR) 7th International Conference on Railway Operations Modelling and Analysis*, Lille, France, April 2017.

Slow orders are imposed when track defects are detected by vehicles equipped with various inspection technologies or visually by train crews and track inspectors (Federal Railroad Administration 2014). The definition of a defect is dictated by the Federal Railroad Administration (FRA) Track Safety Standards or individual railroad track standards and recommended practices. Slow orders are also imposed after the track structure has been disturbed by certain track maintenance activities. Slow orders caused by track disturbance during maintenance typically require speeds to be reduced to 10-20 mph (16-32 km/h) for approximately 0.2 million gross tons (MGT) of traffic while the track structure stabilizes (Selig & Waters 1994). This process is routine and can be included in the cost of maintenance, so it will not be explored in detail in this chapter, although the model presented can be used for determining the associated train delay. Alternatively, slow orders prompted by track defects cannot be explicitly planned for and must be modeled to estimate how frequently they will occur. Due to the uncertainty of when defects will occur, it would be time and cost prohibitive to run simulations for every possible case. This is further complicated when considering slow orders in a maintenance planning optimization model that may not be able to access an external simulation. A complex slow order delay formulation may also substantially increase the optimization model solution time or make it difficult to solve for a true optimum.

To aid infrastructure owners in determining the operational impacts of slow orders and optimize associated maintenance plans, I developed a new model to estimate the expected slow order cost on a given rail line segment. These estimates can be used to aid in planning the timing and location of maintenance, including application in an optimization model.

5.2 Operational impacts of traffic disruptions

Stopping rail traffic or decreasing average train speeds reduces the capacity of a particular line. If rail traffic is low enough, it is possible that headways between trains will be long enough that delayed trains will not affect subsequent traffic. This is not always a safe assumption for North American railroads where flexible operations do not have fixed headways, and multiple trains can bunch together. In addition, the majority of the North American railway network is single track and capacity is less dependent on train headway than it is on the train running time on the single-track sections between passing sidings. Under these conditions, a proper representation of slow order operational impacts needs to consider the effect of cascading train delays. When the location of a planned slow order is known, a rail traffic simulator can be used to determine the operational impacts. For defect-caused slow orders, the exact number and location of slow orders are unknown. Therefore, a general model is necessary to evaluate a wide range of possible scenarios and estimate the resulting operational impact.

5.2.1 Highway delay methods

For delays to vehicular traffic on roadways, the Webster uniform delay model can be used to simulate the impact of stopped traffic (Roess et al. 2004). The basic theory behind this type of delay model is that the delay experienced by each train is the difference between when that train would be processed under normal operations and the time it is processed under the disrupted operations. This methodology is similar to the one Schafer & Barkan (2008) developed for determining accumulated train delay after track outages, except their approach uses discrete trains rather than a continuous approximation. These methodologies must be modified to include a period of diminished operations during the time slow orders are in effect. Graphically, the delay model can be depicted by plotting the cumulative number of trains processed over time for both normal and disrupted operations and calculating the area between the curves (Figure 5.1). While this model is simple, it enables infrastructure owners to make quick calculations either directly or within a larger maintenance optimization framework.

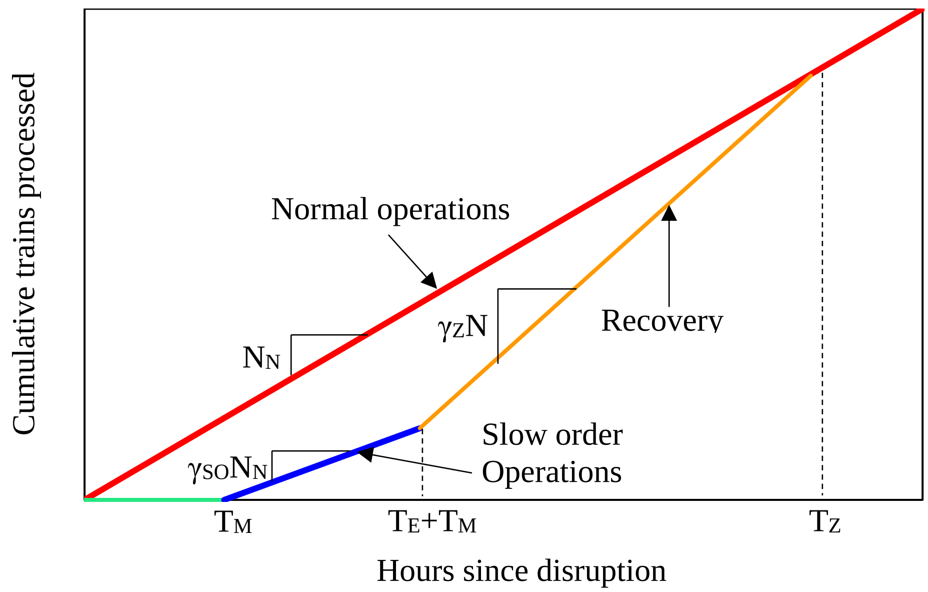

Figure 5.1: Slow order operations

Although slow orders resulting from track defects may not result in stopped trains, they may be implemented after rail traffic is completely stopped for maintenance or repair. Accordingly, the model accounts for an initial period where the line is closed to rail traffic. The number of trains processed during and after a traffic disruption and the total time from the start of the disruption to the point where normal operations resume can be represented mathematically (Equations 5.1 – 5.2).

$$q_T = \begin{cases} 0, & 0 \le t \le T_M \\ \gamma_{SO} N_N (t - T_M), & T_M < t \le T_M + T_E \\ N_N(\gamma_Z (t - T_E - T_M) + \gamma_{SO} T_E), & T_M + T_E < t \le T_Z \\ N_N t, & else \end{cases} \qquad 5.1$$

$$T_Z = (\gamma_Z (T_M + T_E) - \gamma_{SO} T_E) / (\gamma_Z - 1) \qquad 5.2$$

Where:

q_T – number of trains processed after a disruption begins
t – time since a traffic disruption began
T_M – time after the disruption begins that the track is returned to service
γ_{SO} – slow order train throughput adjustment factor
N_N – number of trains processed per hour under normal operations
T_E – slow order duration
γ_Z – recovery operations train throughput adjustment factor
T_Z – time between disruption and resumption of normal operations

During the slow order, reduced train speed decreases capacity and the track segment has a reduced train processing rate. For specific applications, operational experience should guide the adjustment factor calibration to obtain a realistic train-processing rate for specific maintenance circumstances. In the absence of specific operating details, this analysis assumes that the reduction factor will be the ratio of the normal and slow order travel times (Equations 5.3 – 5.5).

$$\gamma_{SO} = T_N/T_{SO} \qquad 5.3$$

$$T_N = L_R/V_N \qquad 5.4$$

$$T_{SO} = \min(T_N + N_{SO}((L_{SO} + L_T)(1/V_{SO} - 1/V_N) + T_{AD}) , L_R/V_{SO}) \qquad 5.5$$

Where:

T_N – time to traverse the route under normal operating conditions
T_{SO} – time to traverse the route with an average number of slow orders in place
L_R – length of the route
V_N – normal average train speed
N_{SO} – number of slow orders in place at a time on the route
L_{SO} – slow order length
L_T – average train length
V_{SO} – slow order speed
T_{AD} – additional time to accelerate and decelerate from and to the slow order speed
Other variables as previously defined

This method considers the condition where, as the number of slow orders increase, trains leaving one slow ordered section are unable to accelerate to the normal operating speed before having to slow down for the next slow order. Under this condition, the entire line is effectively subject to a slow order, although additional defects may develop without further operational impact. Since trains must operate at the lowest maximum allowable speed for any part of the train, the slow order area of influence includes the length of both the slow order and an average train. In North America, where trains are regularly over one mile (1.6 km) in length, this means the amount of track affected by a slow order is much longer than just the slow ordered section.

As with the period during the slow order, the recovery period needs a capacity adjustment factor that should also be based on experience and local operating practices. For the recovery operations period after the slow order is removed, I assumed that rail traffic will operate at maximum capacity until normal operations can resume. Since this maximum capacity will typically be somewhat higher than the normal operating traffic volume, the recovery adjustment factor will be calculated as the inverse of the normal capacity utilization (Equation 5.6).

$$\gamma_Z = 1/R_N \tag{5.6}$$

Where:

R_N – proportion of the operating capacity in use under normal operations

Other variables as previously defined

Similar to the Webster uniform delay model, train delay can be computed from the area between the curves using geometry. In this case, to account for the period of diminished train processing rate during the slow order, the train delay is the difference in the area of triangles O-Z-T_B and T_M-S-T_B on the plot of cumulative trains processed over time (Figure 5.2). The resulting area O-Z-S-T_M is a measure of cumulative train delay during the disruption and can be calculated as the area difference between two triangles (Equation 5.7 – 5.10). The derivation is shown in Appendix E.

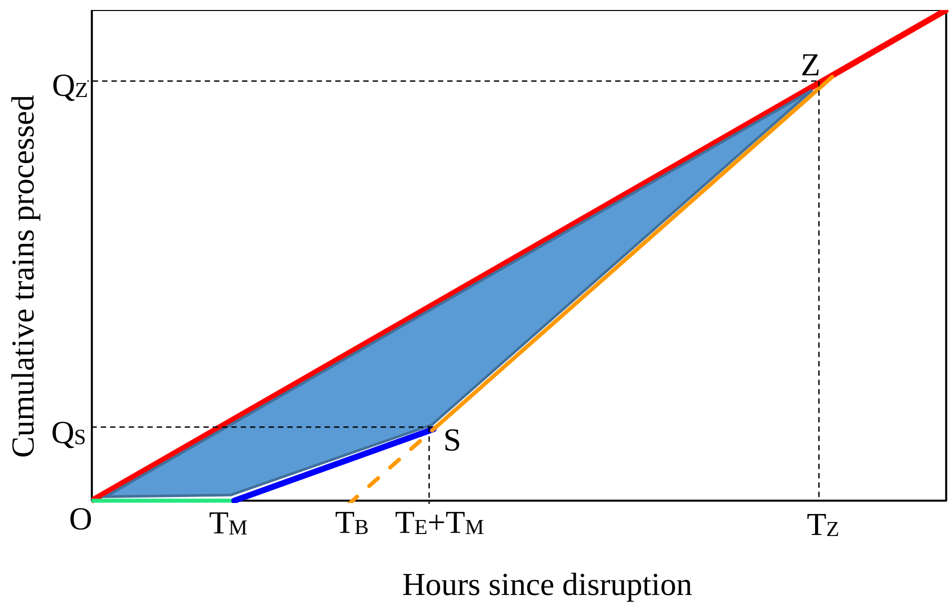

Figure 5.2: Slow order delay area

$T_D = (T_B Q_Z - (T_B - T_M)Q_S)/2$ 5.7

$T_B = T_M + T_E(1 - \gamma_{SO}/\gamma_Z)$ 5.8

$Q_Z = N_N T_Z$ 5.9

$Q_S = \gamma_{SO} N_N T_E$ 5.10

Where:

- T_D – cumulative train delay
- T_B – intercept of the recovery operations line with the x-axis
- Q_Z – number of trains processed between the disruption and resumption of normal operations
- Q_S – number of trains processed during the slow order

Other variables as previously defined

This approach for estimating train delay due to a disruption of rail traffic on a line segment will enable planners to approximate train delay without developing detailed scenarios for a rail traffic simulator. Although this model is designed for predominantly single-track sections, it can also be used to consider other types of traffic disruptions, such as removal of a parallel main line for maintenance or accident recovery. To be applied in this manner, Equations 5.3 – 5.6 need to be altered since the adjustment factors for the reduced service and recovery operations will be more dependent on the type of infrastructure in place. Initial simulations may be necessary to determine the appropriate adjustment factors for use in multiple-track territory. If the route has large sections with multiple tracks, the model may become less applicable since there may be sufficient infrastructure to handle the traffic even if sections of track are removed from service.

5.3 Train delay sensitivity

In the discussion of the model formulation, it was noted that several parameters related to capacity utilization and train-processing rate during the slow order might need to be set based on experience. The sensitivity of the model to these parameters will determine how important it is to obtain precise estimates of their values so as not to introduce excess uncertainty into the calculated train delay. Since the model consists of several levels of equations, it is not immediately obvious what the effect of changing a single value will be. To determine which parameters have the greatest influence on the model output and how train delay varies based on the selected inputs; both single- and two-factor sensitivity analyses were performed.

5.3.1 Single-factor sensitivity

The sensitivity of the model to each factor was examined over a range of typical input values (Table 5.1). The arc elasticity, which controls for the relative magnitude of each input (Allen & Lerner 1934), was calculated for each factor, using the upper and lower bounds in Table 5.1 (Figure 5.3, exact values are provided in Appendix F). For each factor, the average of the bounds was taken as the base condition.

Table 5.1: Arc elasticity bounds

Parameter	Lower bound	Upper bound
Track outage time, T_M (hours)	0	24
Slow order duration, T_E (hours)	0	240
Route length, L_R (mile)	2[1]	200[1]
Individual slow order length, L_{SO} (mile)	0.01[1]	1[1]
Average train length, L_T (mile)	0.5[1]	1.5[1]
Normal train velocity, V_N (mph)	30[1]	80[1]
Slow order train velocity, V_{SO} (mph)	10[1]	30[1]
Number of slow orders, N_{SO}	0	6
Additional acceleration and deceleration time T_{AD} (hours)	0.1	0.5
Trains per hour, N_N	0.1	2
Normal capacity utilization, R_N	0.4	0.9

1. 1 mile = 1.61 km

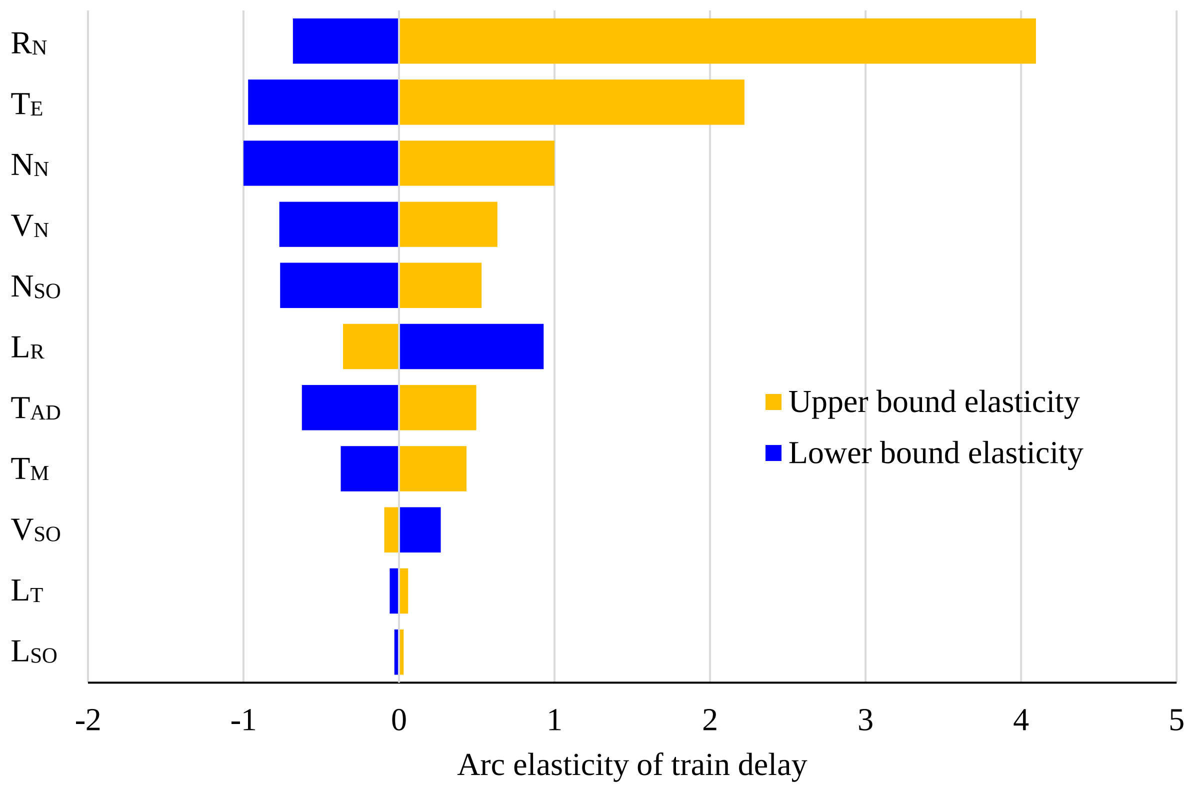

Figure 5.3: Arc elasticity of the delay model

All the parameters tested had the expected elasticity directionality, meaning an increase had the expected effect on the level of train delay. For example, increasing the normal capacity utilization, R_N, which the model is most sensitive to, results in an increased level of train delay, however, the amount of elasticity is not the same for both bounds. This is intuitively correct because if a route is being operated near capacity, there will be less flexibility to recover from a disruption. High levels of excess capacity, indicating low utilization, may not result in substantial levels of cascading delay allowing for a rapid recovery to normal operations. The average slow order duration, T_E, has a similar effect because the longer the slow order is in place, the more trains will be affected and the more time is required for recovery. The slow-order speed, V_{SO}, and route length, L_R, are the two parameters where an increase results in less train delay. For slow-order speed, this is because higher slow-order speeds have less impact on the train-processing rate so fewer trains will be affected. Additionally, for a constant number of slow orders, longer routes will result in a lower proportion of track affected by slow orders. The normal train-processing rate, N_N, is another anomaly since increasing or decreasing the processing rate yields an arc elasticity of one. This is because the train delay is linearly related to the processing rate as shown in Equations 5.9 and 5.10.

5.3.2 Two-factor interactions

Since many of the parameters interact, it is beneficial to see how changing two affects the amount of train delay. In the following illustrative cases, the factors that are not varied remain at the base values from the single-factor sensitivity analysis.

Since the model was most sensitive to track capacity utilization, R_N, and slow order duration, T_E, they were varied first (Figure 5.4). For a given capacity utilization, the train delay increases disproportionately to slow order duration. As the slow order duration increases, the additional train delay between R_N curves also increases, showing the necessity of keeping slow order durations low on highly utilized routes (where R_N will be highest). While this result is

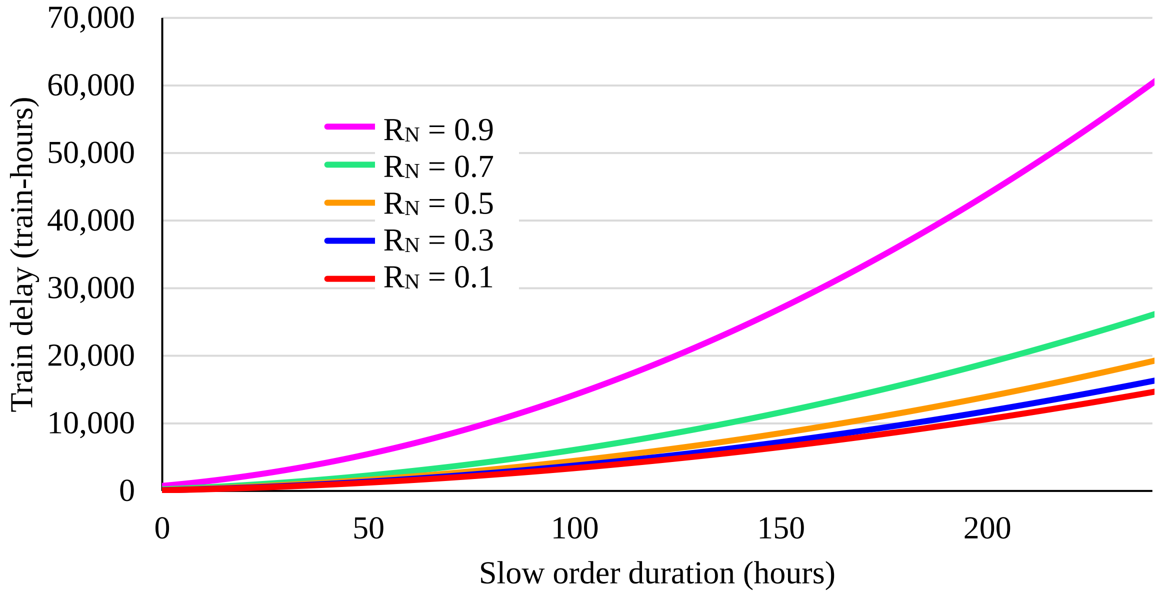

Figure 5.4: Effect of operating capacity and slow order duration on train delay

expected based on intuition and Equations 5.6 – 5.9, quantifying the effects allow for an objective comparison of the costs to operate track at different utilization levels.

Since the normal operating speed, V_N, was the next most sensitive parameter of interest and has direct interactions with the slow-order speed, V_{SO}, they were also varied (Figure 5.5). All of the curves exhibit a discontinuity where the model shifts from having the entire line effectively slow ordered to considering each slow order independently. This occurs because the difference between the normal and slow-ordered travel times is so low that the effect of just a few slow orders will exceed the travel time difference. The slope of the curves after the discontinuity are shallower because additional factors are affecting the travel time when computing the slow order adjustment factor. This relationship may change if the acceleration and deceleration time is changed to be a function of the normal and slow order speeds.

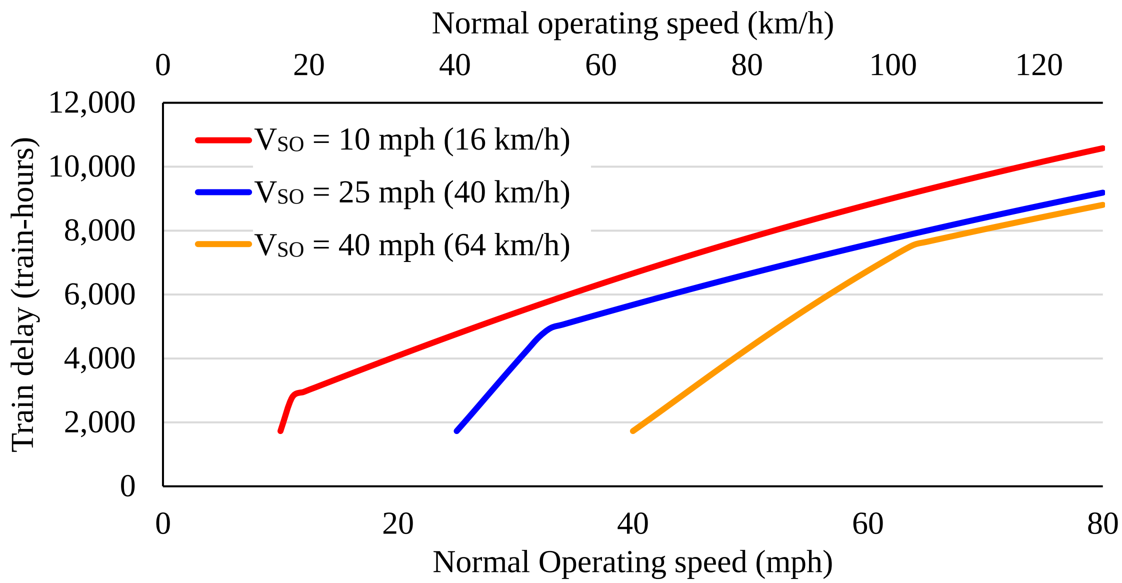

Figure 5.5: Effect of normal operating and slow order speeds on train delay

Since routes with high utilization typically have higher operating speeds, the normal speed and capacity utilization, V_N and R_N, were also varied together (Figure 5.6). As the normal capacity utilization approaches one, the train delay begins to asymptote. Using this delay model, if the route is already being operated at full capacity before a disruption, the route will not be able to recover to normal operations after a disruption without annulling, combining, or rerouting trains. At lower normal capacity utilization levels, the curves are almost linear until a R_N value of about 0.6 is reached. Above that level of capacity utilization, routes with higher normal operating speeds will begin to asymptote more quickly due to the difference in normal and slow-order speeds. This, and the results in Figure 5.4, validates the industry practice of keeping track utilization below 75-percent to ensure adequate recovery capacity (American Railway Engineering and Maintenance-of-Way Association 2012a).

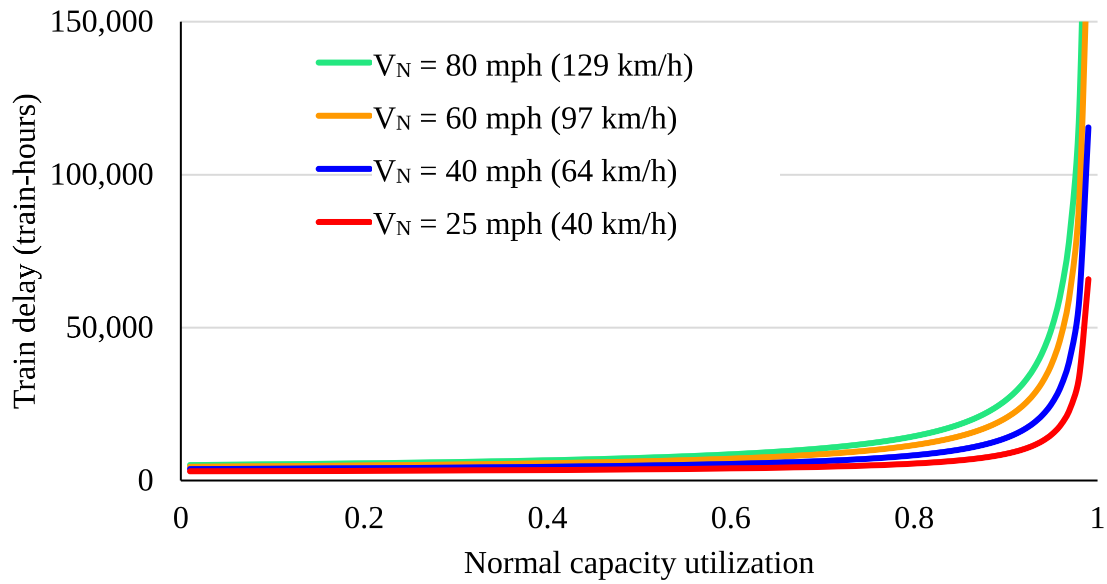

Figure 5.6: Effect of normal operating speed and capacity utilization

5.4 Application to slow orders

Risk is comprised of both likelihood and consequence (Ang & Tang 2007). While Section 5.3 detailed a model of the train delay consequence of slow orders, this section discusses how the likelihood of slow order occurrence affects train delay. Probabilistic models can be used to determine the average annual defect rate per mile. If there are few enough defects that there is a very low probability of more than one slow order occurring at one time on the route, then the delay associated with one slow order can be computed (N_{SO} = 1) and multiplied by the expected number of slow orders on the route during the year. As the defect rate increases, it is more likely that two or more defects, and accompanying slow orders, will be in place concurrently. While the probability of a specific number of defects occurring simultaneously can be calculated using a Poisson distribution, the amount of time traffic is disrupted, T_Z, will vary based on the number of defects. The difference in disruption time makes it difficult to make comparisons for the total amount of slow-order-induced delay over a given year. Since slow orders are only imposed after a defect is identified during an inspection, this can be simplified by dividing the year into inspection intervals. For this model to be valid, the inspection interval must be at least as long as the longest recovery time, T'_Z, to ensure traffic has recovered before new slow orders are applied. The longest recovery time will be associated with the condition where the entire line is effectively slow ordered and can be found by calculating Equation 5.2 with the number of slow orders in place (Equation 5.11).

$$N'_{SO} = \left\lceil \frac{L_R}{(L_{SO} + L_T)\left(\frac{1}{V_{SO}} - \frac{1}{V_N}\right) + T_{AD}} \left(\frac{1}{V_{SO}} - \frac{1}{V_N}\right) \right\rceil \qquad 5.11$$

Where:

N'_{SO} – minimum number of slow orders resulting in the entire line being effectively slow ordered

Other variables as previously defined

The expected amount of train delay can then be calculated (Equations 5.12 – 5.13).

$$T'_D = \frac{1}{T_I}\left(\sum_{i=0}^{N'_{SO}-1} \left(\frac{\left(\widehat{N}_{SO}\right)^i}{i!} T_D(N_{SO} = i) \right) + T_D(N_{SO} = N'_{SO}) \left(1 - \sum_{i=0}^{N'_{SO}-1} \frac{\left(\widehat{N}_{SO}\right)^i}{i!} \right) \right) \qquad 5.12$$

$$\widehat{N}_{SO} = R_{SO} L_R T_I \qquad 5.13$$

Where:

T'_D – average annual slow order delay

T'_Z – longest slow order disruption time

R_{SO} – average annual number of slow orders per mile

$\widehat{N}_{SO}$ – average annual number of slow orders on the route after an inspection based on the Poisson distribution

T_I – rail flaw inspection interval

Other variables as previously defined

A computationally simpler approach is to calculate the train delay using the equations in Section 5.2 and the expected number of slow orders that will have developed on the line between inspections, $\widehat{N}_{SO}$. The single-inspection delay would be multiplied by the number of inspections during the year to get the annual slow order delay. These two methods, termed the weighted average delay and average slow order methods respectively, will be compared using an adaptation of the Orringer (1990) rail defect model to see the relative differences in expected levels of delay.

The Orringer (1990) rail defect model was modified to predict the expected number of detected defects per mile based on the accumulated tonnage on the rail, inspection interval, and historical ratio of service to detected defects (Equation 5.14). Service defects are those that cause the rail to break, while detected defects are found through rail flaw inspections, such as ultrasonic testing. Only detected defects will be addressed here because service defects require more extensive remedial actions (Federal Railroad Administration 2014). While the model is dated, it is still used by the FRA to recommend rail flaw detection intervals (Volpe Center 2014), and the parameter values are the most recent that could be found in the literature. It is also similar to the approach of Liu et al. (2014) and Liu & Dick (2016) for estimating the cost of rail defects. New models are in development that could be adapted for application here (Davis et al. 2016).

$$R_{SO,R}(y) = N_{Rail}\left(e^{-\left(\frac{yN_A}{\beta_R}\right)^{\alpha_R}} - e^{-\left(\frac{(y+1)N_A}{\beta_R}\right)^{\alpha_R}}\right)\Big/\big(1+\lambda(\Delta N-\theta)\big) \qquad 5.14$$

Where:

- $R_{SO,R}$ – annual detected rail defect rate per mile
- N_{Rail} – number of rail sections per mile
- y – years since capital maintenance was performed
- N_A – annual tonnage (MGT)
- ΔN – average tonnage between rail inspections (MGT)
- θ – minimum inspection interval (10 MGT (Orringer 1990))
- λ – proportionality factor (0.014 (Orringer 1990))
- α_R – Weibull shape factor (3.1 (Davis et al. 1987; Liu et al. 2014))
- β_R – Weibull scale factor (2150 (Davis et al. 1987; Liu et al. 2014))

Orringer's original formulation was modified to use the cumulative distribution function, rather than a probability density function, making the model more accurate and computationally simpler. It was also assumed that the defects would develop uniformly through the year rather than weight the defects more heavily at the end of the year. This simplification was made because Liu et al. (2014) showed that weighting the number of defects more heavily at year's end does not make a material difference in defect costs.

The train delay model described in Equations 5.1 – 5.14 were applied to a hypothetical route with length, L_R, of 100 miles (160 km), normal operating speed, V_N, of 40 mph (64 km/h), handling 30 MGT of freight traffic annually, N_A. This traffic level equates to approximately one freight train every two hours, N_N (Association of American Railroads 2015), with train length, L_T, of one mile (1.6 km). The normal capacity utilization, R_N, is taken as 0.65, which provides sufficient excess capacity to recover from maintenance and other disruptions (Cambridge Systematics 2007).

When a defect is detected, a slow order is implemented with speed, V_S, of 30 mph (48 km/h), length, L_{SO}, of 0.1 miles (0.16 km), and duration, T_E, of 24 hours. The speed reduction is a common FRA remedial action for moderate sized internal rail defects. The defects also have to be re-tested every 24 hours while the defect remains in place (Federal Railroad Administration 2014), so it was assumed that on average, the slow orders would remain in place that long. Although it is common practice in North America to replace approximately 20-foot (6 m) sections of rail surrounding the defect (American Railway Engineering and Maintenance-of-Way Association 2012b), temporary track condition information in North America is communicated in tenth-of-a-mile increments, so that is the smallest practical length of track a slow order can be applied over (Federal Railroad Administration 2005). The direct cost to repair a rail defect was assumed to be $859 (Liu et al. 2014), and the rail inspection interval, ΔN, was taken as 15 MGT, or two inspections per year. The cost of train delay was based on the results in Chapter 3 for manifest traffic where delay would not result in lost shipments and was taken as $950 per train hour. For the parameters of this case study, it was assumed that all trains operate at the maximum speed, but average operating speeds could also be used.

The three methods of calculating the total annual slow order delay mentioned above will be illustrated. Five years after new rail is installed, the defect rate, R_{SO}, is expected to be approximately 0.05 defects/mile-year (0.03 defects/km-year). This would equate to five slow orders occurring throughout the year on the 100-mile (160-km) route, or an average of 2.5 slow orders after each inspection. Using the assumption that the inspections for different parts of the route would be performed on different days, we could assume that all five slow orders occurred independently. Using the equations in Section 5.2, the delay for a single slow order is 12.5 train-hours per slow order or 62.3 train-hours per year. Using Equations 5.2 – 5.5, 5.11, and 5.13, we can compute the expected number of slow orders on the line, $\widehat{N}_{SO}$, as 2.5. Using Equation 5.12, the weighted average delay is 29.8 train hours per inspection interval for a total train delay of 60.5 train-hours per year. This is less than ten percent different from the 65 train-hours of delay per year for the average slow order method. Although the first method is more conservative than the weighted average method, it does not allow an analyst to consider the interactions between individual slow orders, so it will not be examined further.

Using Equations 5.1 – 5.11 and 5.14, the slow order rate and the expected direct and delay slow order costs can be calculated for the period over which rail could be expected to be in service (Figure 5.7). Initially, the direct costs are much lower than the delay costs for either delay computation approach. This is largely due to the difference in delay cost versus the cost to repair

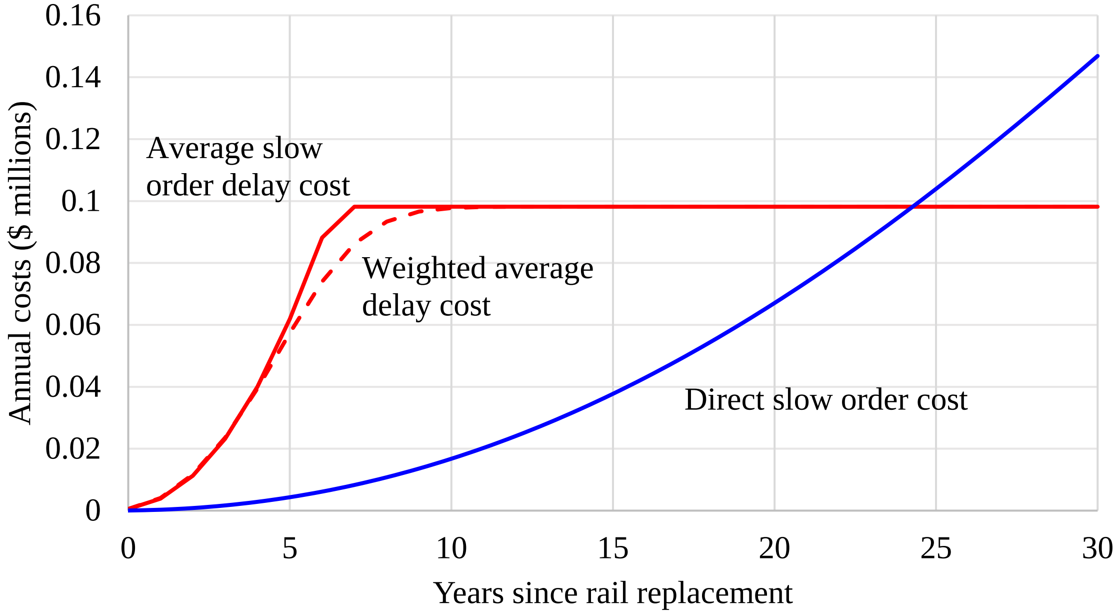

Figure 5.7: Comparison between direct and delay slow order costs using both expected number of slow orders and weighted average of slow orders

a single defect. Due to the overlapping influence of the slow orders, eventually the delay costs plateau, but the direct costs continue to rise because each defect must be repaired, and the direct costs eventually exceed the delay costs. Assuming traffic levels and train delay costs are constant, reducing the maintenance response or recovery time for a given defect rate will reduce the total time traffic is disrupted, and thus the amount of train delay caused by the slow order.

The two methods for calculating train delay result in similar results. The exception to this is around the transition from considering each slow order independently and slow ordering the entire route. The weighted average cost curve has a more gradual growth because even at the higher defect rates, there is a relatively high probability of having a single slow order at a time. Eventually, both methods converge to the plateau delay cost because there is a low probability of having few enough slow orders in place to consider them independently.

By combining the slow order direct cost with one of the delay cost curves, maintenance planners can see the total slow order costs over time and how adjusting maintenance timing changes the total slow order cost. Performing capital maintenance earlier will reduce the slow order costs but has drawbacks in terms of asset utilization and increases in maintenance frequency. Infrastructure owners can balance the costs of disruptions over time with the cost to perform maintenance that will prevent slow orders and reactive defect repair, sometimes referred to as spot maintenance. If spot maintenance is made more efficient, effective, and timely, it can reduce the disruption-caused train delay costs in addition to direct maintenance cost because they will not need to be performed as frequently.

5.5 Conclusions and future work

In this chapter, I presented a new closed-form model for determining the train delay effects of traffic disruptions. This model is intended to be used by infrastructure managers for maintenance planning. The simplicity of the model will make it more accessible to planners and easier to apply within a larger maintenance planning optimization framework. The model also helps quantify the effects of how the route is operated before, during, and after a disruption. If the line is usually operated near capacity, it will take much longer to recover from a disruption, and the train delay will be much higher than if there is ample excess capacity. Additionally, if the line is normally operated at capacity, operations may not be able to recover without reducing the number of trains through annulments or rerouting. This is especially true if the slow order duration is long or the normal operating speeds are high. Also, when the difference between normal and slow order speed is low, it does not take many defects to overcome the travel time difference, resulting in the entire line being slow ordered.

Quantifying the impact of slow-order caused train delay and the nature of the operational effects of slow orders provides insight on how to reduce the overall cost of the rail system by factoring these effects into a capital maintenance plan. The two methods to calculate average delay provide similar results, but the simpler approach using the expected number of slow orders is more conservative during the transition between treating slow orders independently and effectively having a slow order over the entire line. This could be a problem when planning maintenance in this time frame, so the disparity should be investigated to see if it makes a substantial difference in the cost for a particular application. If the slow order delay model is applied to an optimization model, the average slow order method is beneficial due to its lower computational complexity. Both methods also demonstrate the phenomenon where slow order costs plateau due to overlapping slow order areas of influence. Maintenance improvements will be most cost effective if they enable the route to avoid the plateau region, through either improved response time or reducing the number of defects. Cost analyses will help determine which routes would benefit from maintenance improvements and determine cutoffs for where preventative maintenance should be performed based on risk tolerances. Another way to reduce the delay effects of service disruptions is to add capacity to the line. While many infrastructure owners treat capacity expansion as a last resort, quantification of train delay accumulation can help determine where that may be more cost-effective than investments in additional maintenance crews or equipment because traffic will still be able to flow freely.

Future research will explore how train delay and defect probability can be incorporated into an optimization model for scheduling track maintenance over a network. This will require probabilistic models for approximating the failure rate associated with other track components such as crossties and ballast. Specifically with delay modeling, additional work can expand our understanding of the slow order and recovery adjustment factor calibration to make them more general and allow for direct use on double track routes or in situations where the normal traffic can be rerouted or combined to mitigate the impact of a disruption.

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CHAPTER 6.

PREDICTING THE OCCURRENCE AND COST OF TEMPORARY SPEED RESTRICTIONS ON NORTH AMERICAN FREIGHT LINES [1]

6.1 Introduction

Average train speed of the major North American railroads are a key metric of network fluidity and are reported to Association of American Railroads (2016) on a weekly basis. Lower average train speeds increase the number of crews, locomotives, and railcars required to move a given volume of freight and increase other associated operating costs. Given the impact of slowing trains, it is not surprising that temporary speed restrictions, or “slow orders,” are a strategic concern. It is difficult to isolate the costs specific to slow orders. The analysis in Chapter 4 is among the first attempts to quantify the expected impact of slow orders or other disruptions. That analysis found that slow orders related to timber crossties do not have sufficient impact on railroad operations to materially influence track maintenance and operating decisions. This lack of quantitative support for industry practice indicated that further research was required to determine how slow orders affect network operations. One way to estimate future impacts is through risk analysis, which considers both the probability, or frequency, and the impact of an event (Ang & Tang 2007). This chapter will build on the operational impact work in Chapter 5 by estimating the rate of slow order occurrence related to rail, crosstie, and ballast defects.

Slow orders are applied to a track segment when it is found to be unsuitable for operation at the posted maximum allowable speed (MAS). These conditions arise after the track structure has

[1] This chapter is modified from Lovett, A.H., C.T. Dick and C.P.L. Barkan. 2017 (in press). Predicting the occurrence and cost of temporary speed restrictions on North American freight lines. In: *Proceedings of the International Heavy Haul Conference*, Cape Town, South Africa, September 2017.

been disturbed for maintenance or when track defects are detected. Slow orders caused by track disturbance typically require speeds to be reduced to 10-20 mph (16-32 km/h) for approximately 0.2 million gross tons (MGT) of traffic while the track stabilizes (Selig & Waters 1994). This process is a routine part of maintenance activities such as tamping and crosstie renewal and can be incorporated into the cost of these activities during the maintenance planning process. Therefore, slow orders for track disturbed by routine maintenance activities are not considered in detail in this chapter.

Defect-caused slow orders are unexpected events that are difficult to predict and explicitly consider in maintenance planning. Various analytical and probabilistic models can estimate the frequency of track defects that require the railroad to impose a slow order. In this chapter, the rate of defects resulting in slow orders is termed the "slow order rate." The estimated average slow order rate on a specific track segment can be used to determine the expected cost of slow orders and unplanned maintenance due to track defects in a given year. Understanding how the slow order rates change over time, and the factors that influence them, will also give insight into how capital maintenance timing affects the total cost of track ownership and operation. In this chapter, I examine how to predict the slow order rate for three major track components: rail, crossties, and ballast, and apply it to capital track maintenance planning. Ballast defects include alignment and surface defects, and maintenance activities to repair these defects are classified as ballast maintenance.

Although railroads have their own maintenance standards that establish criteria for when to impose slow orders, they are also subject to government-defined standards intended to ensure a minimum level of safe train operations. Since the United States Federal Railroad Administration (FRA) Track Safety Standards (TSS) are typically the same as the Canadian regulations and apply to more miles of track, they will be taken as representative of typical North American operations (Transport Canada 2011; Federal Railroad Administration 2014). Generally, the track geometry tolerances in the TSS vary by track class with each having a prescribed MAS. Internal rail defects are the exception because the type and size of the defect, rather than the operating speed, determine the remedial action. As the track class, and associated MAS, increases the allowable tolerances decrease. When the measured in-service track geometry exceeds tolerances, prescribed remedial actions are required on that track segment until maintenance to correct the defect is completed (Federal Railroad Administration 2014).

6.2 Slow order costs

Although this chapter will focus on the slow order occurrence rate, it is helpful to understand the costs associated with slow orders since both rate and consequence are required to estimate risk. As with most disruptions to rail traffic, slow orders result in both direct and indirect costs that vary with the nature of the defect as well as maintenance and operational factors.

6.2.1 Direct maintenance costs

Direct costs are those associated with performing localized maintenance to repair the defect and remove the slow order, including labor, materials, and equipment. This localized, or "spot," maintenance is typically not intended to return the track to a perfect state. Spot maintenance is also relatively inefficient due to its small scale, short work windows, and reactive nature (Shimatake 1997; Esveld 2001; Zoeteman 2004; Burns & Franke 2005; Grimes & Barkan 2006; Lovett et al. 2015).

Direct slow order costs follow a traditional risk formulation since the expected costs are the defect rate times the cost per defect. These costs are largely dependent on the track component associated with the defect since different types of remedial action are required for each component. For internal rail defects, a new section of rail, approximately 20 feet (6 m) long, is welded in to replace the section containing the defect (American Railway Engineering and Maintenance-of-Way Association 2012). Ballast-related defects are typically corrected by localized tamping. Other components, such as crossties, require local replacement of a sufficient number of the defective units to meet the required specifications (Riley & Strong 2003; Federal Railroad Administration 2014). Railroads usually track the cost of these activities and can apply them in maintenance planning.

6.2.2 Indirect costs

Train delay is the primary indirect cost for slow orders. Chapter 5 presented a closed-form model for estimating train delay associated with a given number of slow orders and operating conditions. Since this formulation includes the slow order rate, risk is effectively the output. It also considers the interaction between slow orders, the effects of which will be discussed further in Section 6.4. After the amount of train delay is computed, it must be multiplied by a train delay cost that considers the operational characteristics of traffic operating on the line like those developed in Chapter 3.

6.3 Prediction models

To predict the approximate number of slow orders on a track segment in a given year, probabilistic models were used to determine the average annual defect rate per mile. While interactions between track components may increase the local occurrence of defects once one component fails, no models were found that consider these interactions. Therefore, I treat each of the major track components independently.

6.3.1 Rail slow order prediction

There are a variety of rail defect types identified by the FRA, each with one or more possible remedial actions based on defect severity (Federal Railroad Administration 2014). This analysis will focus on transverse fissures as most rail defects are given this categorization until they are removed from service for further examination (Sperry Rail Service 1999). The detected rail defect model developed in Chapter 5, based on Orringer (1990), can be applied here. The Orringer model focuses on detail fractures, a subset of transverse fissures, because they were the most frequent cause of rail breaks when the analysis was performed (Liu et al. 2014), however, the concept can be applied to any type of rail defect. Only detected defects will be addressed here because service defects, or “service failures”, may require more extensive remedial actions including halting service on the line (Federal Railroad Administration 2014). For convenience, Equation 5.14 is repeated here (Equation 6.1).

$$R_{SO,R}(y_R) = N_{Rail}\left(e^{-\left(\frac{y_R N_A}{\beta_R}\right)^{\alpha_R}} - e^{-\left(\frac{(y_R+1)N_A}{\beta_R}\right)^{\alpha_R}}\right)\Big/ 1 + \lambda(\Delta N - \theta) \qquad 6.1$$

Where:

- $R_{SO,R}$ – annual detected rail defect rate per mile
- N_{Rail} – number of rail sections per mile (273 (Orringer 1990))
- y_R – years since rail replacement was performed
- N_A – annual tonnage (MGT)
- ΔN – average tonnage between rail inspections (MGT)
- θ – minimum inspection interval (10 MGT (Orringer 1990))
- λ – proportionality factor (0.014 (Orringer 1990))
- α_R – Weibull shape factor (3.1 (Davis et al. 1987; Liu et al. 2014))
- β_R – Weibull scale factor (2150 (Davis et al. 1987; Liu et al. 2014)).

As mentioned in Chapter 5, this model is dated, but it is still used by the FRA to determine rail flaw inspection intervals (Volpe Center 2014). New research is ongoing to develop new rail defect prediction models that can be used for this purpose (Davis et al. 2016).

6.3.2 Crosstie slow order prediction

The FRA TSS require a minimum number of crossties in good condition within each 39-foot section of track based on the MAS and track curvature (Federal Railroad Administration 2014). The Forest Service Products Curve (FSPC) can be used to determine the failure probability of timber crossties as a function of the ratio of crosstie age to average life (MacLean 1957), but this only gives the probability of failure for crossties of a single age. The nature of crosstie renewals is that only one-quarter to one-third are replaced during each cycle, leading to multiple cohorts of varying ages. The model presented in Chapter 4 provides a process for determining the probability of an FRA TSS defect occurring over a 39-foot section of track given a certain amount of time has elapsed since a crosstie renewal and is repeated here for convenience (Equation 6.2 – 6.4).

$$R_{SO,T}(y_T) = \left(P_{39}(y_T+1) - P_{39}(y_T)\right) \times \frac{5280}{39} \tag{6.2}$$

$$P_{39}(y) = 1 - \sum_{F} \prod_{j=1}^{k} \binom{n_j}{i_j} p_j^{i_j}(y) \left(1 - p_j(y)\right)^{n_j - i_j} \tag{6.3}$$

$$p_j(y) = 1 - \exp\left[-\left(\frac{y + (j-1)c}{\beta_T A}\right)^{\alpha_T}\right] \tag{6.4}$$

Where:

- $R_{SO,T}$ – annual number of crosstie related slow orders per mile
- y_T – number of years since crosstie renewal
- F – set of failed crosstie combinations not resulting in an FRA TSS defect in a given 39-foot (12-m) section of track
- k – number of crosstie age groups
- n_j – number of crossties in age group j

i_j – number of failed crossties in age group j
c – time between capital crosstie replacements
A – average crosstie life
α_T – crosstie Weibull shape factor (4.56)
β_T – crosstie Weibull scale factor (1.02)
Other variables as previously defined

Equation 6.4 represents the Weibull distribution approximation of the FSPC used as the occurrence probability for the Binomial distribution in Equation 6.3.

Since the original FSPC found failure rates based on the age of a crosstie relative to the average life, the shape and scale factors in Equation 6.4 do not need to consider the operating conditions directly because they can be factored into the average crosstie life. This model assumes regular replacement cycles where a set number are replaced per mile in each renewal. If the replacement cycle or number of crossties replaced is not constant, Equation 6.4 will need to be modified to consider the initial age of each cohort at the beginning of the analysis period.

6.3.3 Ballast slow order prediction

Similar to rail defects, there are a variety of defect types associated with the track geometry surface and alignment, but all track geometry defects attributable to ballast defects require the same general types of remedial actions and corrective maintenance (Federal Railroad Administration 2014). Previous research in this area has focused on the standard deviation of various alignment measurements (Shimatake 1997; Oh et al. 2006; Chang et al. 2010), however, North American track geometry tolerances are based on absolute deviations (Federal Railroad Administration 2014), so a new model was developed based on the methodology of Alemazkoor et al. (2015) (Equations 6.5 – 6.7). The data set used was originally released for determining defect progression and did not explicitly include maintenance data (INFORMS Railway Applications Section 2015). Maintenance timing was assumed to have occurred if an initial inspection found a FRA TSS defect, but no defects were detected on the next inspection. The data were then fit to a Weibull distribution.

$$R_{SO,B}(y_B) = \left(P_{200}(y_B + 1)\right) \times \frac{5280}{200} \tag{6.5}$$

$$P_{200}(y) = 1 - \exp\left[-\left(\frac{y * 365}{\beta_B}\right)^{\alpha_B}\right] \tag{6.6}$$

$$\beta_B = \exp(\boldsymbol{\Phi X}) \tag{6.7}$$

Where:

$R_{SO,B}$	–	annual number of ballast-related slow orders per mile
$P_{200}(y)$	–	probability of a given 200-foot section of track developing one or more surface or alignment related defects at time y
y_B	–	years since undercutting was performed
α_B	–	ballast shape factor (1.088)
β_B	–	ballast scale factor (8,862)
$\boldsymbol{\Phi}$	–	row vector of coefficients
X	–	column vector of explanatory variables.

Since there is no defined average life of a ballast defect, as is the case in the FSPC, the scale factor will need to vary based on the operating conditions. This can be done by having the scale factor be a function of the specific explanatory variables that are most significant for a particular route or section of track (Mishalani & Madanat 2002; Kleinbaum & Klein 2012; Alemazkoor et al. 2015). Since the dataset was not designed specifically for this analysis, only the time since capital maintenance was last performed was used to determine the slow order rate. Including some other explanatory variables, such as track class and tonnage, resulted in slightly more accurate predictions, but I determined a simpler model outweighed the marginal increase in accuracy (See Appendix G for further details). If a more detailed dataset is available, other explanatory variables can be included. Unlike rail and crossties, typical ballast maintenance to eliminate track geometry defects does not involve replacing the ballast section outright with new material. Since the ballast is not truly "new," it is assumed that ballast defects will return each subsequent year that capital maintenance (undercutting) is not performed. This means that all expected ballast defects since capital maintenance was performed need to be considered in a cumulative manner, rather than just those occurring for the first time in a given year as in the rail and crosstie models.

6.4 Case study

The models discussed in Section 6.3 were applied to a hypothetical 100-mile (160 km) section of 40 mph (64 km/h) track (FRA Class 3) handling 30 MGT annually. Based on industry averages, this tonnage level equates to approximately 12 trains per day (Association of American Railroads 2015). Average train length is assumed to be one mile. Rail defect slow orders result in a speed reduction to 30 mph (48 km/h), while crosstie and ballast-related slow orders result in 25 mph (40 km/h) maximum speeds (Federal Railroad Administration 2014). This case study assumes all trains operate at the MAS but average operating speeds could also be used. Rail defect inspections occur every 15 MGT and on average rail defects cost $895 to repair (Liu et al. 2014). As in Chapter 4, crossties have a 20-inch (51-cm) spacing on-center, 30-year average life, and a nine-year renewal cycle. Crosstie defects are corrected by replacing three crossties for a total cost of $285 (Zeta-Tech Associates Inc. 2006). Ballast slow orders cost $1,200 to repair based on an industry source for the cost of spot tamping. Inspections for crossties and ballast occur once per week (Federal Railroad Administration 2014). All slow orders are applied on the 0.1-mile (0.16-km) section of track surrounding the defect. The duration of rail, crosstie, and ballast slow orders are assumed to be one, four, and three days, respectively. As in previous chapters, I assume that normal operations use 65% of a line's capacity (Cambridge Systematics 2007), accelerating and decelerating into and out of slow orders adds an additional 15 minutes to the run time, and train delay costs $950 per train-hour.

6.4.1 Direct, delay, and total cost comparisons

The defect rates for each component under the above case study parameters were calculated over a range of conditions expected during the duration of a typical maintenance cycle for that component (Figure 6.1). The "defect repair" curves correspond to the equations in Section 6.3. These curves can be compared to the "no repair" curves that show what the theoretical defect rate would be if the defects were not repaired. The ballast curve is the exception since I assumed the defect rate will include both the new defects that develop during the year and all the previously maintained ballast defects that will reoccur that year. If the ballast defects were not maintained, the number of defects would increase at approximately the same rate but the severity would increase. Realistically, components degrade until an acute failure, such as a rail break, occurs so the "no repair" situations will not be examined further.

Comparing the component specific defect repair curves reveals that they each perform differently. Rail defects exhibit a gradual growth that stays relatively low compared to the other components. Crossties perform quite differently; there are almost no defects during the first 12

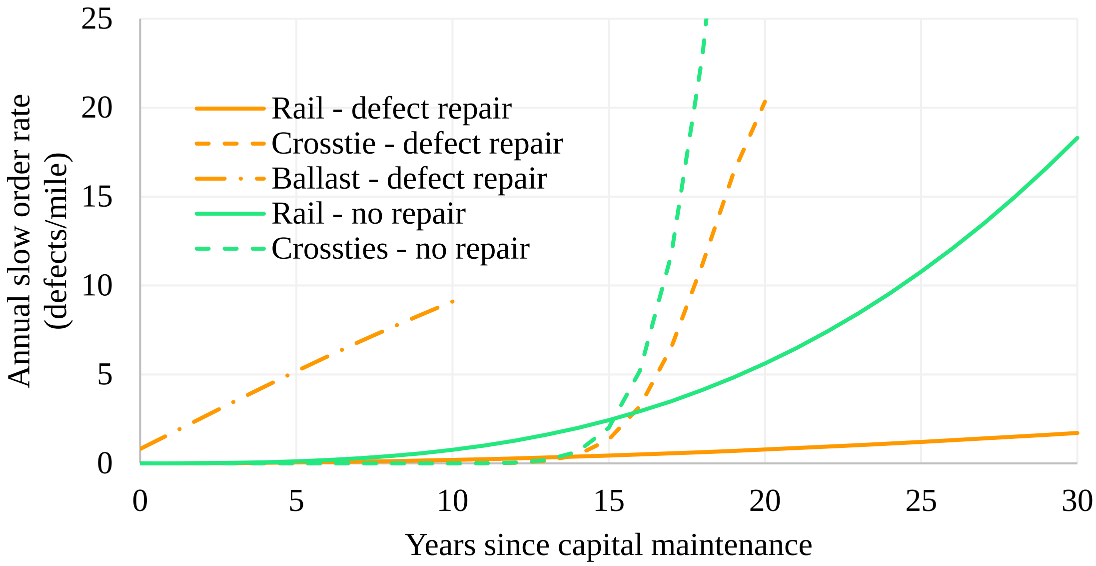

Figure 6.1: Slow order defect rate for the major track components with and without spot maintenance

years after their renewal followed by a steep increase thereafter. This is because Class 3 track requires eight crossties per 39 feet (12 m) to be free of defects (Federal Railroad Administration 2014). For a track defect to develop, almost all the crossties installed before the most recent renewal would need to fail. Once the crossties from the two most recent renewals have a larger probability of failure, the compounded failure probability increases rapidly. This also explains why the analysis in Chapter 4 found that crosstie slow order risk would not materially influence maintenance decisions because I only calculated slow order costs until the ninth year after a crosstie renewal.

Further insight is gained by comparing the total, direct, and delay slow order costs for each component (Figures 6.2 – 6.4). Each plot shows the region where the defect rate increases until there are enough defects that the entire route is effectively subject to speed restrictions, as evidenced by the plateau in the delay cost curve. As discussed in Chapter 5, the shape of the delay cost curve, including the plateau location, changes based on the traffic, train performance, and slow order characteristics.

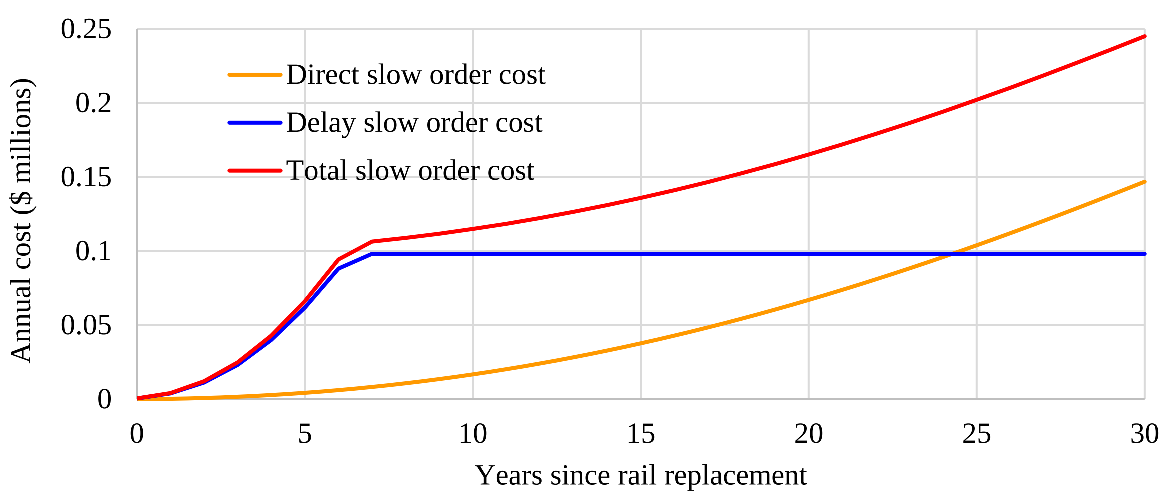

Figure 6.2: Annual cost of rail-related slow orders vs. years since capital maintenance

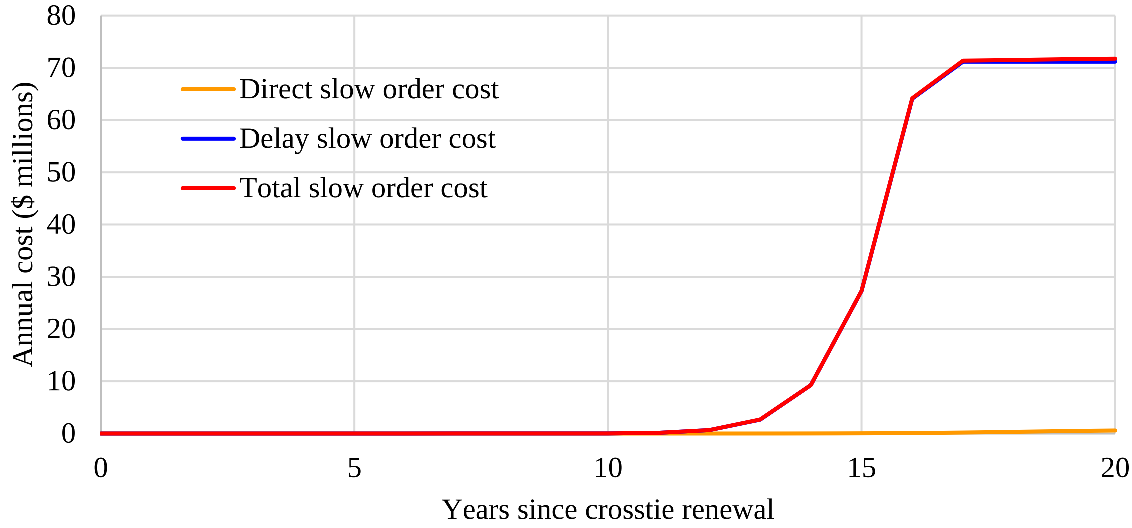

Figure 6.3: Annual cost of crosstie-related slow orders vs. years since capital maintenance

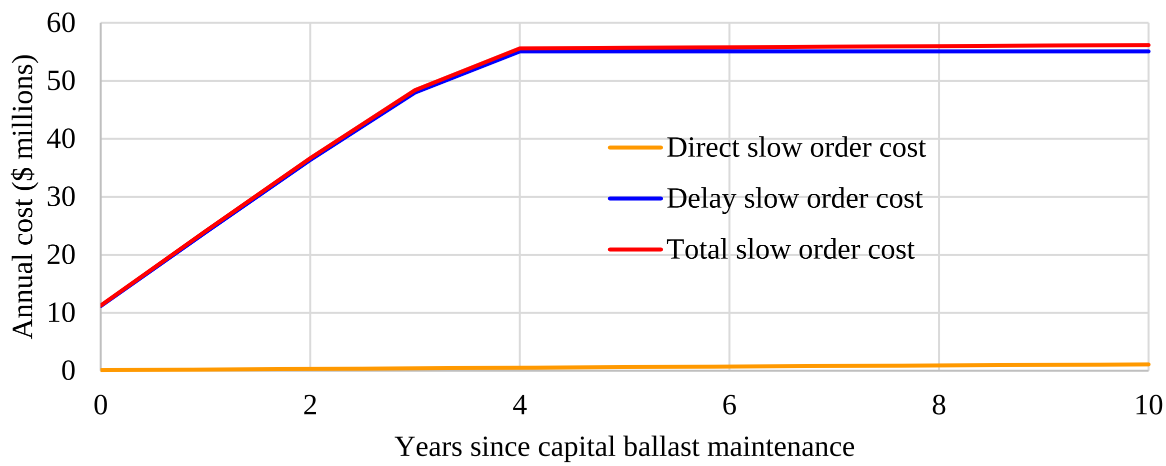

Figure 6.4: Annual cost of ballast-related slow orders vs. years since capital maintenance

For rail (Figure 6.2), the train delay costs are on the same order of magnitude compared to the direct costs since the slow order duration is short and the inspections occur only twice per year. The other extreme is observed for crossties (Figure 6.3) and ballast (Figure 6.4) where the accumulated delay renders the direct costs of repair almost negligible. An increase in delay costs would be expected since the crosstie slow orders are left in place longer. This disproportionate increase is in line with the analysis in Chapter 5, but a key difference is the number of inspections taking place during the year. The rail slow orders are concentrated after only two inspections and are only in place for 24 hours, so there is a long period of time when no slow orders are in effect. For crossties and ballast, a new set of slow orders are being placed every week, so even though the delay associated with a single slow order differs by only one order of magnitude, the delays are incurred much more often.

6.4.2 Comparison of alternate maintenance timings

Although it is interesting to look at how the slow order costs change over time, a primary benefit of these curves is to aid in capital maintenance planning. In Figures 6.2 – 6.4, the area under the total cost curve represents the slow order cost for each component in a given planning period. Performing capital maintenance during the planning period will reduce the slow order cost associated with the new component during subsequent years but the savings need to be balanced against the expense of performing capital maintenance. This can be done by comparing the slow order costs for different capital maintenance schedules within the planning period (Figures 6.5 – 6.7).

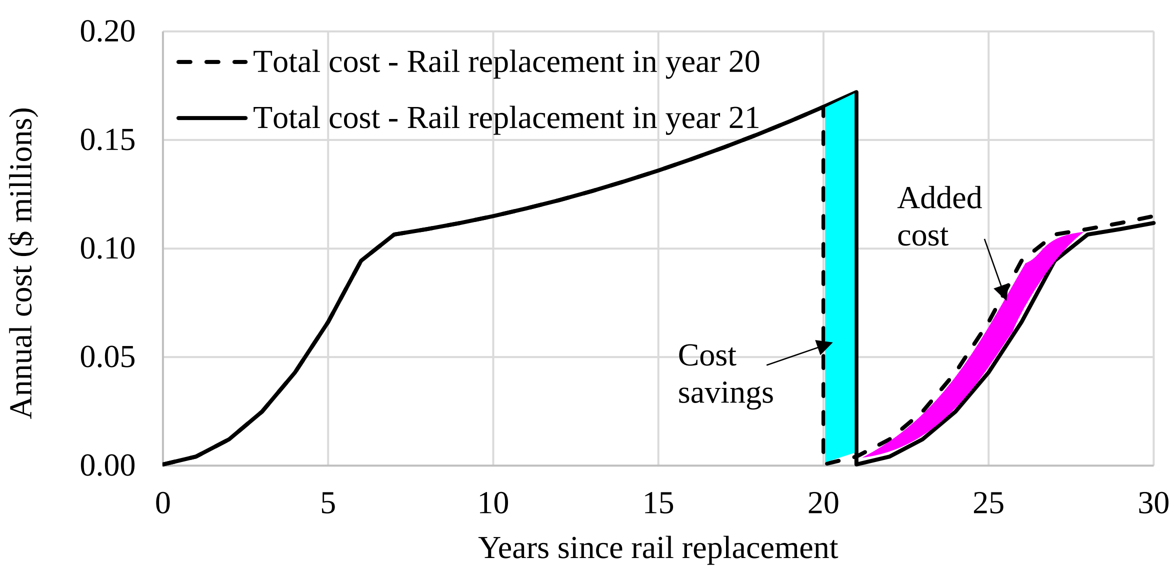

Figure 6.5: Rail slow order cost under different rail replacement schedules

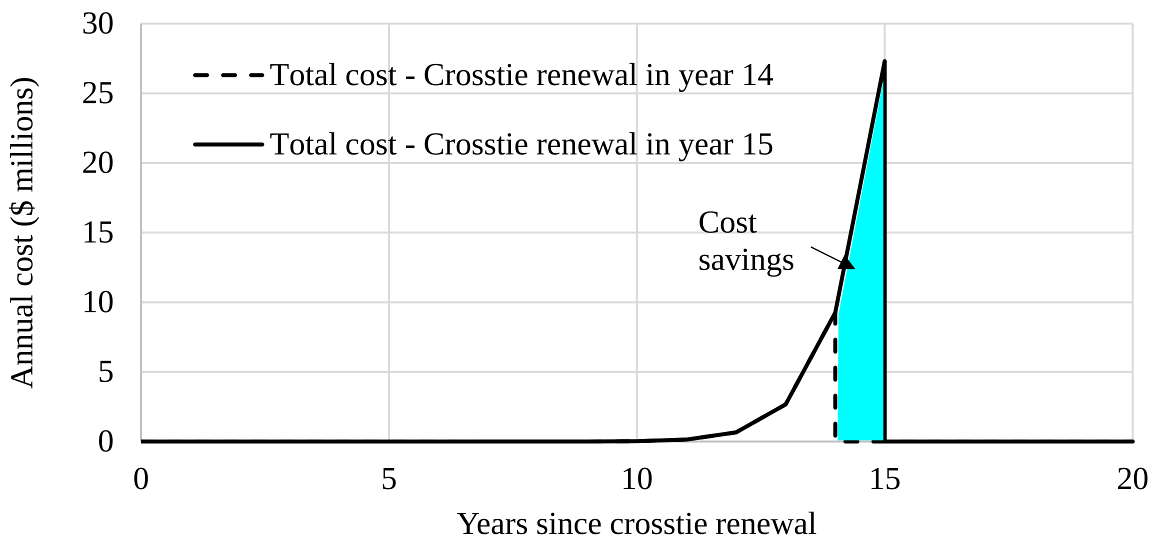

Figure 6.6: Crosstie slow order cost under different crosstie renewal schedules

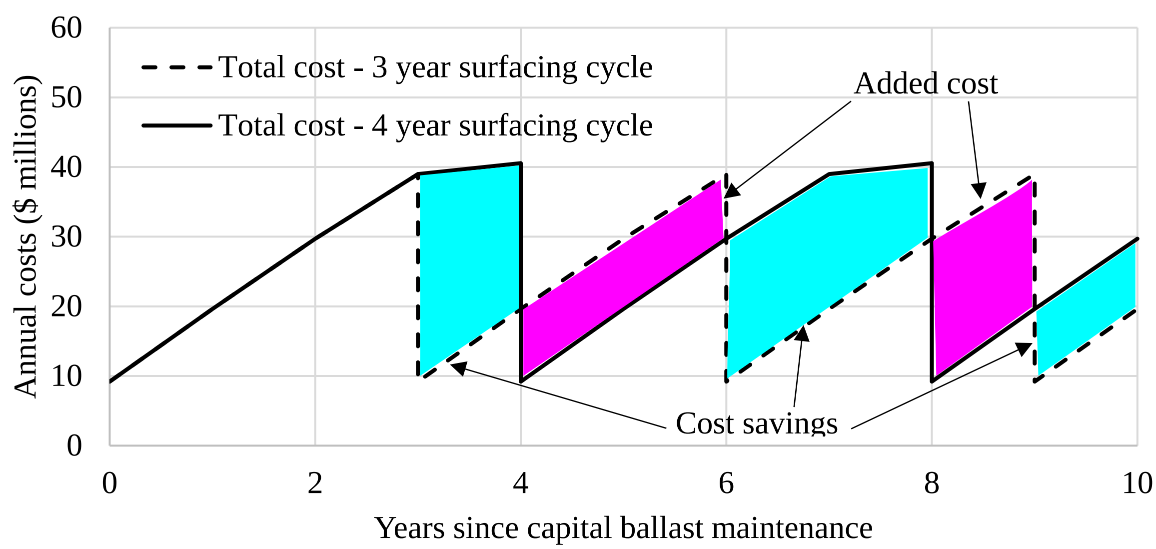

Figure 6.7: Ballast related slow order cost under different capital surfacing schedules

For rail (Figure 6.5) and crossties (Figure 6.6), performing maintenance earlier initially reduces the slow order cost by a noticeable amount. Comparing the slow order costs for rail in later years shows that the annual cost is higher for the earlier replacement curve. That is to be expected since it has been longer since capital maintenance was performed. Over time, the higher slow order cost combined with costs to perform capital maintenance earlier may counteract the initial slow order savings, showing that a longer-term perspective is required for maintenance planning.

Comparison of ballast maintenance schedules (Figure 6.7) provides a different perspective because capital maintenance is performed multiple times within the 10-year planning period illustrated. Since the three-year undercutting interval would require more maintenance events than the four-year interval, the capital costs will be higher, further offsetting the slow order cost reduction. This shows that the selection of the planning window is also an important factor when comparing proposed maintenance schedules since it will influence the number of times maintenance will need to be performed.

6.5 Conclusions and future work

In this chapter, I present an approach to predicting the cost of slow orders and how to use them for maintenance planning. One of the key findings of this research is the impact of train delay on the cost of slow orders. In almost all cases, train delay costs are larger than the direct cost to repair the track defect causing the slow order. The exception being in the rail case where the defect rate continues to grow after the delay costs have plateaued, and the two costs are within an order of magnitude of each other. For the crosstie and ballast slow orders, the delay costs are high enough that the direct costs are orders of magnitude lower than the delay costs even after the delay costs have plateaued. A driving factor behind these different behaviors is the number of inspections during the year. Fewer inspections coupled with short slow order duration results in the rail delay costs being very low, but as either the number of inspections or the slow order duration increases, the delay costs can rise rapidly. The substantial contribution of train delay to total costs shows how important it is to consider the operational impacts of slow orders and track defects when planning maintenance intervals.

The effects of train delay and the nature of the operational impact of slow orders provide key inputs to a maintenance plan. While performing capital maintenance earlier will reduce the immediate slow order costs, additional costs are incurred in later years after the track components have degraded. Quantification of the slow order impacts allows the capital maintenance plan to be optimized by balancing the slow order and capital maintenance costs. Additionally, if spot maintenance is made more efficient, effective, and timely it can reduce the overall costs and recurrence of slow orders while increasing the time between capital maintenance activities.

One area where this work can be made more robust is by gathering new data from the railroads and either validating these findings or developing new models that reflect the current quality of materials and maintenance practices. A new analysis could take advantage of "big data" techniques such as machine learning that were not available for development of the rail and crosstie models referenced in this chapter. Analyzing new data would also allow for comprehensive slow order models that consider the condition and maintenance history of the entire track structure rather than a single component. Applying the findings and methodology from this research to new probabilistic models will allow railroads to more effectively optimize their maintenance strategy by using a more holistic planning approach.

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CHAPTER 7.

QUANTIFYING THE TRADE-OFF BETWEEN TRACK MAINTENANCE COSTS AND DISRUPTION RISK USING PROBABILISTIC RISK ASSESSMENT

7.1 Introduction and background

Each year the major North American railroads spend billions of dollars maintaining their infrastructure to ensure it operates safely and efficiently (Association of American Railroads 2017). Typically, normal, or spot, repairs are performed on a regular basis by local crews to extend the time between large-scale capital maintenance events (Grimes & Barkan 2006). Despite these investments, failures of the railway infrastructure still occur, causing accidents and other service disruptions (Association of American Railroads 2016a).

When railroads plan capital track maintenance, there needs to be a balance between fully utilizing the service life of track components and reducing the risk of failures. To analyze this trade-off, railway practitioners require additional knowledge and approaches to better quantify the change in failure, or disruption, risk associated with advancing or deferring capital projects. Probabilistic risk assessment (PRA) has been used in many industries to quantify the risk of failures and some efforts have been made to incorporate it into cost analysis (Abolhelm et al. 2014). The methodology developed in this chapter uses PRA tools to quantify the risk of disruptions due to track component failures so that it can be included in track maintenance planning. Two primary types of disruptions due to track component failures are considered in this chapter: slow orders and acute disruptions.

As discussed in Chapters 5 and 6, slow orders, or temporary speed restrictions, are a substantial concern for railroads. A slow order is placed on a section of track when it is deemed unsuitable for train operation at the normal posted maximum speeds. This usually occurs because either the track has degraded beyond set tolerances or track support has been disturbed during maintenance activities. The allowable tolerances, as well as maximum allowable speeds, are based on the track classes defined by the Federal Railroad Administration (2014a). When the tolerances are exceeded, the track class and corresponding maximum operating speed are reduced until the tolerances are met. Slow orders increase the cost of train operations and decrease the capacity of the line. By reducing capacity, the operational impacts of slow orders can affect trains that arrive after the slow order has been removed.

For the purposes of this research, acute disruptions are defined as service interruptions due to track component failures that require rail traffic to stop. Acute disruptions include derailments or component failures, such as a rail break, where the track is impassable until the situation is remedied. While derailments are relatively rare, they tend to have high financial and public relations consequences (Liu et al. 2012; Lovett et al. 2013; Federal Railroad Administration 2014b). Derailments can have a wide variety of causes ranging from track irregularities to human error, but in this chapter, I will focus on track-caused derailments since those are directly affected by maintenance timing. Rail breaks and other component failures are less costly but still disrupt the system during repairs and may lead to derailments if not detected before the passage of a train. There have been few attempts to link acute disruption rates and their consequences to the scheduling of track maintenance activities. This chapter quantifies the disruption risk in a way that can support a risk-based maintenance planning methodology.

7.2 Literature review

Many industries use risk to consider the impact of failures in both system design and operations (Modarres et al. 2017). Including risk allows for better understanding of the potential cost implications of disruptions and their balance against the cost of preventive measures (Garrick 2008). Some argue that private, for-profit industries have an incentive to avoid preventive safety measures, such as maintenance, while others believe that safe operations are good for business (Osborn & Jackson 1988; Madsen 2013). Studies examining relationships between profitability and safety have reached inconsistent conclusions (Madsen 2013; Abolhelm et al. 2014). Madsen (2013) notes that typical organizational risk analysis compares known investments for unknown benefits, but reductions in safety investments are the opposite situation. When reducing safety investments, the potential savings of the decision are easily quantified but the negative consequences are unknown and potentially very large. North American railroads consistently identify safety as their number one priority (Association of American Railroads 2016b), and increased infrastructure investment has a statistically significant relationship with decreased accident rates (Dennis 2002). These factors indicate that railroads are unlikely to decrease maintenance expenditures with the expectation of improved corporate financial outcomes.

Understanding how specific decisions affect risk is critical for its inclusion in cost analysis. A number of authors have discussed the costs associated with preventive safety measures (Nicolet-Monnier & Gheorghe 1996; Slovic & Weber 2002; Liu et al. 2015; Liu & Dick 2016; Qian & Lin 2016). In the specific application of railroad track maintenance, the known added cost of performing additional maintenance will decrease the disruption risk, but it is difficult to quantify the exact risk-reduction benefit. In this chapter, I demonstrate how risk analysis can help quantify the potential benefits of those measures.

Risk analysis in the transportation industry is most commonly applied to hazardous materials shipments. Early PRA applications in transportation compared shipment modes for energy products and radioactive materials (McSweeney et al. 1975; Williams & Hall 1976; Elder et al. 1978; Geffen et al. 1978, 1980, 1981; Rhoads et al. 1980). Nayak et al. (1983) analyzed railway hazardous materials shipments with a focus on the number of railcars releasing their contents and the amount released rather than the monetary cost of an incident. More recently, several model frameworks have included disruption costs (Fabiano et al. 2002, 2005; Gheorghe et al. 2005), while others have focused specifically on finding minimal risk routes (Cassini 1998; Verma 2009, 2011; Verma & Verter 2010; Siddiqui & Verma 2015; Azad et al. 2016). A few of these models explicitly consider how costs, and potentially routing, would change if risk mitigation efforts were used (Verma 2009; Verma & Verter 2010; Siddiqui & Verma 2015; Azad et al. 2016).

Other railway industry decisions have been aided by various forms of risk analysis. Recent emphasis on expanded passenger rail service in the United States has spurred research to assess the risk of passenger and freight trains sharing track or operating in relatively close proximity (Cockle 2014; Lin & Saat 2014; Lin et al. 2016). The desire to cost-effectively improve grade crossing safety has led to analysis of the financial aspects of incident risk when determining where to make improvements (Saccomanno et al. 2004; Chadwick et al. 2013, 2014; Pyrgidis et al. 2016). The concept of using the expected number of incidents and finding the best way to use limited funds is similar to track maintenance planning where the cost to execute projects must be balanced against the associated disruption risk reduction. Liu et al. (2014) and Liu & Dick (2016) optimized rail flaw inspection intervals by minimizing the combined inspection and risk costs. This approach can be modified to optimize rail replacement timing by minimizing disruption costs.

Despite these applications of risk assessment in the rail industry, more information is required to relate the effects of track maintenance to disruption risk. The model in Chapter 4 was an initial attempt to apply disruption costs but was limited by the availability of data and suitable slow order delay models. The following section will expand on some of these concepts to develop a more robust cost analysis using PRA concepts.

7.3 Methodology

In the classical PRA format, an event tree is used to examine the possible operating conditions for each train that traverses a small section of track (Figure 7.1). In this case, we assume that a disruption requires a defect in the track. Each top event has an occurrence probability or a fault tree associated with it (Modarres et al. 2017). One example fault tree from the overall event tree in Figure 7.1 is the probability that a defect present in the track section has

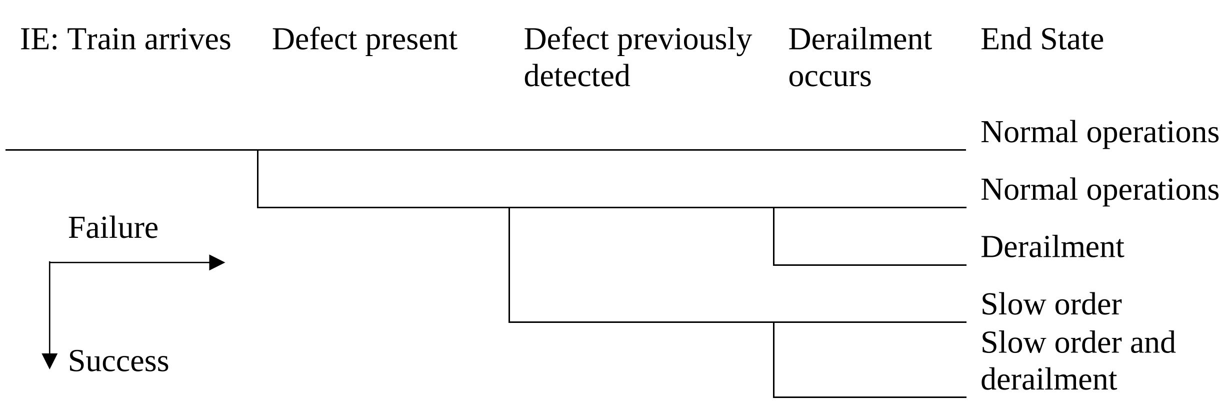

Figure 7.1: Sample event tree for a single train

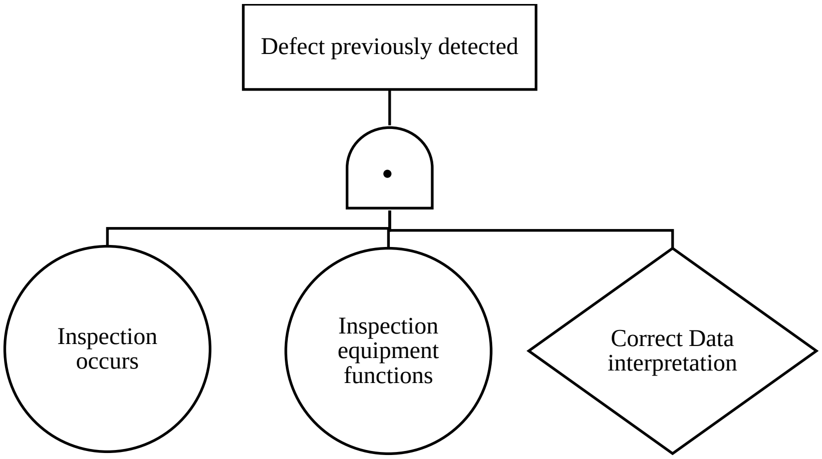

Figure 7.2: Defect detection fault tree

been detected and a slow order put in place before the train arrives (Figure 7.2). A slow order is only implemented if an inspection occurs between the time of defect formation and train arrival, the inspection equipment functions properly, and the inspection data are interpreted correctly. The probability of correct data interpretation can be further modeled using human reliability analysis (HRA) or represented using historical data. Although event trees are roughly chronological, the physical event that creates a disruptive condition may have occurred before the initiating event (Modarres et al. 2017), and defect detection is an example of this. An inspection would have to occur before the train arrives, but the presence of a previously detected defect would not affect train operations until a train traverses that section of track.

These simplified event and fault trees do not reflect the full complexity of the railroad track system. As discussed in Chapter 6, there are multiple track components that can cause slow orders or derailments, each with different disruption characteristics. Furthermore, multiple disruptions may occur at the same time. Each of these probabilities could be identified from either experience or manufacturer testing, but more in-depth analysis, such as HRA, could also be applied if sufficient data are available. From this analysis, importance measures could be calculated for each basic event allowing for adjustment of maintenance plans to reduce the risk. Reliability of each major track component (rails, crossties, and ballast) could also be calculated based on defect rates and combined to determine the reliability of the track section.

Unfortunately, performing this level of detailed analysis requires a large amount of data that the railroads consider confidential or may not be routinely collecting. Additionally, in most railroad operations, delay due to disruptions can cascade to delay subsequent trains, further making traditional reliability analysis difficult.

To simplify the analysis, I propose consideration of disruption costs accumulated over one year on a route. The general formulation is comprised of maintenance, train delay, slow order, and acute disruption costs in each year of the planning period (Equation 7.1). Each individual cost category is described in more detail in the subsequent sections.

$$C_{Total} = \sum_{j} \left(\frac{1}{(1+r)^{j}} \left(C_{Mj} + C_{DMj} + C_{SOj} + C_{Xj} \right) \right) \tag{7.1}$$

Where:

- C_{Total} – total cost associated with the track performance during the planning period
- j – index of the years in the planning period
- r – discount rate
- C_{Mj} – cost to perform maintenance in year j
- C_{DMj} – cost of delay due to maintenance activities in year j
- C_{SOj} – slow order cost in year j
- C_{Xj} – average acute disruption cost in year j

7.3.1 Maintenance costs

Although maintenance costs are deterministic, their timing directly affects disruption risk, so these costs are a critical part of a risk-based cost analysis. Direct costs and disruption risk must be balanced to ensure that maintenance is not performed more often than necessary while keeping disruption costs at an acceptable level. These costs should consider both the direct cost of performing maintenance and potential savings from scheduling some maintenance activities in the same year (Equation 7.2). Surfacing costs are incurred during both capital crosstie and ballast maintenance, so if both were scheduled during the same year, the cost of one surfacing can be saved.

$$C_{Mj} = L_R\left(\sum_i \left(x_{ij}C_{Ji}\right) - x_{Crosstie,j}x_{Ballast,j}C_S\right) \tag{7.2}$$

Where:

L_R – route length
i – index for track components, {Rail, Crossties, Ballast}
x_{ij} – binary indicator for maintenance being performed on component i in year j
C_{Ji} – direct cost per mile (1.6 km) to perform maintenance on component i
C_S – direct cost per mile (1.6 km) to surface the track
Other variables as previously defined

Performing maintenance also disrupts rail traffic on the line. Trains must wait until they can proceed along the route, and the delay accumulates until traffic returns to normal. As with direct maintenance costs, delay must also consider potential economies that may reduce the amount of time the track is out of service (Equation 7.3).

$$C_{DMj} = C_D L_R\left(\sum_i x_{ij}T_{DMij}Q_{Ji} - x_{Crosstie,j}x_{Ballast,j}Q_S T_{DS,j}\right) \tag{7.3}$$

Where:

C_D – train delay cost
T_{DMji} – train delay per window for component i in year j based on Chapter 5 (train-hours)
Q_{Ji} – number of work windows per mile (1.6 km) required to maintain component i
Q_S – number of work windows per mile (1.6 km) required to surface the track
$T_{DS,j}$ – train delay per window for surfacing in year j based on Chapter 5 (train-hours)
Other variables as previously defined

7.3.2 Slow order costs

The methodology presented in Chapters 5 and 6 are used to estimate the slow order costs for each track component. A shortcoming of this method is that each of the major railroad track components is treated separately due to the lack of data to relate their interactions. Preliminary research has shown a relationship between the performance of each component and its propensity to develop defects (Zarembski et al. 2016), but it is not conclusive or detailed enough to compute dependency. As further data become available, these relationships can be quantified for use in later analyses.

A second shortcoming is that the method assumes slow orders of different types will not occur in the same location at the same time. The assumption that all slow orders are separate events with no overlap will cause the model to overestimate the number and effect of the disruptions. However, the probabilities of overlap are low until the defect density is high enough that slow orders of the same kind have overlapping areas of influence. This overlapping effect is considered in the delay accumulation model, so it need not be explicitly considered in this analysis.

For maintenance planning, both the direct cost to repair a defect and the train delay costs must be included (Equation 7.4). Local maintenance crews only know to impose a slow order or repair a track defect after an inspection. While every defect that develops during the year must be maintained and are relatively independent, as discussed in Chapter 5, there can be interactions between slow orders that are in effect at the same time on a route. Since slow orders are only implemented after an inspection, the associated delay cost will consider the average number of defects discovered in an inspection (Equation 7.5).

$$C_{SOj} = \sum_i \left(L_R R_{SOij} C_{SODi} + \frac{C_D T_{DSOij}}{T_{Iij}} \right) \tag{7.4}$$

$$N_{SOij} = R_{SOij} L_R T_{Iij} \tag{7.5}$$

Where:

R_{SOij} – slow order rate per mile-year (1.6 km-year) according to the models in Chapter 6 for component i in year j

C_{SODi} – direct cost to correct a slow order causing defect in component i

T_{DSOij} – train delay based on Chapter 5 with parameters associated with this line and N_{SOij} slow orders of type i in year j

N_{SOij} – average number of slow order causing defects detected in an inspection for component i in year j

T_{Iij} – inspection interval for component i in year j

Other variables as previously defined

7.3.3 Acute disruptions

Acute disruption costs include the cost of track-caused accidents and track component failures, such as rail breaks, that cause rail traffic to stop. This analysis uses derailment rate as a proxy for the accident rate because over 99% of track-caused accidents are derailments (Federal Railroad Administration 2014b).

For rail breaks and rail-caused derailments, an event tree can be developed to represent the progression of a rail break from defect to derailment or slow order (Figure 7.3). The event tree assumes that a detected defect is repaired and will not result in a broken rail and that a rail break

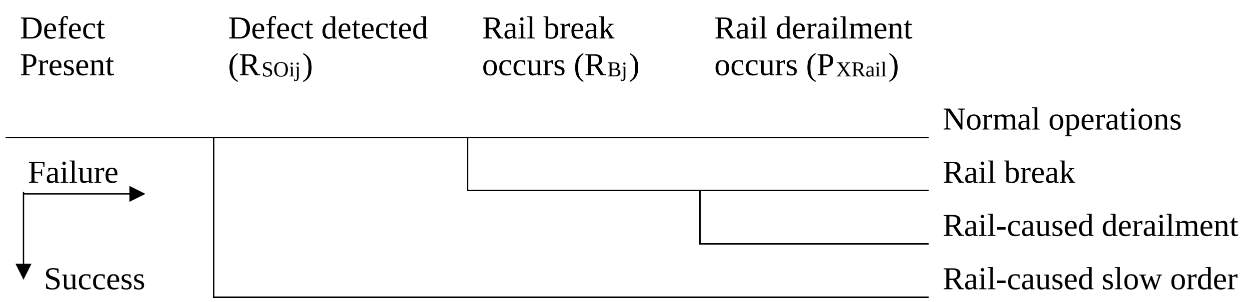

Figure 7.3: Single rail defect event tree

is required for a rail-caused derailment (Liu et al. 2014). The rail-caused disruption risk can be found by following the respective branches on the event tree following the methodology of Liu et al. (2014) (Equation 7.6). Liu & Dick (2016) approximated the frequency of rail breaks and derailments using the Orringer (1990) model. That model was simplified to align with the formulation for calculating the rail-caused slow order rate used in Chapters 5 and 6 that is also based on Orringer (1990) (Equation 7.7).

$$C'_{XRail\,j} = R_{Bj}\left(\left(C_{B,M} + C_D T_{DBj}\right) + P_{XRail}\left(C_{XD,Rail} + C_D T_{DXj}\right)\right) \qquad 7.6$$

$$R_{Bj} = N_{Rail}\lambda\left(\Delta N_j - \theta\right)\left(e^{-\left(\frac{N_{Aj}y_{Rail,j}}{\beta_{Rail}}\right)^{\alpha_{Rail}}} - e^{-\left(\frac{N_{A,j}\left(y_{Rail,j}+1\right)}{\beta_{Rail}}\right)^{\alpha_{Rail}}}\right)\Big/ 1 + \lambda\left(\Delta N_j - \theta\right) \qquad 7.7$$

Where:

$C'_{XRail\,j}$ – rail-break related costs per mile (1.6 km)
R_{Bj} – annual rail break rate per mile (1.6 km)
$C_{B,M}$ – direct cost to repair a rail break ($2140 (Liu et al. 2014))
T_{DBj} – train delay due to rail breaks in year j based on Chapter 5
P_{XRail} – probability of a derailment given a rail break (0.0084 (Zarembski & Palese 2005))
$C_{XD,Rai}$ – average broken-rail-caused derailment cost ($1,016,834 (Liu et al. 2014))
T_{DXj} – train delay costs due to a derailment in year j based on Chapter 5
N_{Rail} – number of rail sections per mile (1.6 km) (273 (Orringer 1990))
λ – proportionality factor (0.014 (Orringer 1990))
ΔN_j – average tonnage between rail inspections in year j (Million gross tons (MGT))
θ – minimum inspection interval (10 MGT (Orringer 1990))
N_{Aj} – annual tonnage in year j (MGT)
$y_{Rail,j}$ – years since rail replacement in year j
α_{Rail} – Weibull shape factor (3.1 (Davis et al. 1987; Liu et al. 2014))
β_{Rail} – Weibull scale factor (2150 (Davis et al. 1987; Liu et al. 2014))
Other variables as previously defined

The relationship between track quality and derailment rate is not as well understood for crossties and ballast, so a proxy value is needed. Preliminary analysis estimated the derailment rate using the proportion of derailments caused by the failure of specific components, the accident rate, and an assumed track degradation rate (Lovett et al. 2015). This analysis was updated using more current derailment rates and the percentage of track slow ordered, rather than an assumed degradation rate. The expected derailment risk can be calculated as the weighted average of the derailment risk at the normal and slow ordered track classes based on the percentage of track that is expected to be slow ordered (Equations 7.8 and 7.9). Since the slow orders may overlap, it is necessary to explicitly limit the slow order proportion to one.

$$C'_{Xij} = P_{SOij} C_{X(l-1)i} R_{X(l-1)} P_{X(l-1)i} + \left(1 - P_{SOij}\right) C_{Xli} R_{Xl} P_{Xli} \tag{7.8}$$

$$P_{SOij} = \min\left(L_{SO} R_{SO,ij} T_{E,i}, 1\right) \tag{7.9}$$

Where:

C'_{Xij} – accident risk for component i in year j
C_{Xli} – average derailment cost due to component i in track class l
R_{Xl} – derailment rate on track class l
P_{Xli} – proportion of derailments on track class l caused by component i
P_{SOij} – proportion of the track slow ordered during the year
L_{SO} – length of an individual slow order
T_{Ei} – average length of time a slow order due to component i is left in place
Other variables as previously defined

The complete acute disruption cost can then be calculated (Equation 7.10).

$$C_{Xj} = L_R \left(C'_{XRailj} + \frac{N_A}{1000} \sum_{i \neq Rail} C'_{Xij} \right) \tag{7.10}$$

7.4 Case study

To investigate how maintenance timing affects the costs associated with a maintenance plan, the methodology described in the previous section was applied to a case study. The line being analyzed is 100 miles (160 km) of Class 3 (40 mph (64 km/h) maximum allowable freight train speed) track with 30 MGT of annual traffic. This tonnage corresponds to approximately 12 trains per day (Association of American Railroads 2015). System and component parameters are based on industry averages (Table 7.1 and Table **7.2** respectively).

Table 7.1: System parameters

Parameter	Value
Discount rate[1]	9.61%
Train delay cost[2]	$950 per train-hour
Slow order length[3]	0.1 miles[7]
Class 3 derailment rate (R_{Xl})[4]	0.11 per billion-gross-ton-miles[7]
Class 2 derailment rate ($R_{X(l-1)}$)[4]	0.22 per billion-gross-ton-miles[7]
Work window length	7.5 hours
Surfacing direct costs (C_S)[5]	$15,000 per mile[7]
Surfacing windows (Q_S)[6]	0.33 per mile[7]

1. (Surface Transportation Board 2016)
2. Average value for manifest traffic based on the analysis in Chapter 3
3. (Federal Railroad Administration 2005)
4. (Liu et al. 2017)
5. Using average cost from ACW Railway Company (2015) and amounts from Chrismer (1988)
6. For a 7.5 hour window (Burns & Franke 2005a, 2005b)
7. 1 mile = 1.6 km

Table 7.2: Selected case study parameters

	Rail	Crosstie	Ballast
Direct slow order repair cost (C_{SODi}) [1]	$859	$285	$1,200
Average inspection interval in days (T_{Ii})[1]	182.5	7	7
Years since last capital maintenance (y_{ij})	15	3	2
Normal maintenance cycle (years)	20	9	3
Slow order duration in days (T_E)[1]	1	4	3
Class 3 Derailment cost (C_{Xli})[2]	$994,019	$1,063,301	$994,019
Class 2 Derailment cost ($C_{X(l-1)i}$)[2]	$615,967	$728,313	$615,967
Class 3 derailment proportion (P_{Xli})[3]	-	4.11%	13.76%
Class 2 derailment proportion ($P_{X(l-1)i}$)[3]	-	8.08%	15.55%
Direct cost (C_{Ji})[4]	$184,000[4]	$52,000[4]	$138,000[4]
Windows per mile (Q_{Ji})[5,6]	1.59	1.39	1.21

1. From Chapter 6
2. Based on analysis of the FRA accident database (Federal Railroad Administration 2014b) and modified using an accident cost multiplier (Kalay et al. 2011) and train delay costs based on a 24-hour outage using Chapter 5
3. (Federal Railroad Administration 2014b)
4. Based on Burns & Franke (2005b), with inclusion of surfacing after crosstie and ballast work and materials costs. Rail and ballast materials costs are from ACW Railway Company (2015), ballast quantities are drawn from Chrismer (1988), and crosstie costs are drawn from Burns (1989) and inflated to 2015 dollars by a factor of 1.136 (Bureau of Labor Statistics 2017).
5. (Burns & Franke 2005b)
6. 1 mile = 1.6 km

The base maintenance plan uses the normal maintenance cycles in Table 7.2 (Table 7.3). With minor modifications to the schedule, maintenance planners can take advantage of the economies of performing crosstie and ballast work in the same year. Three alternative schedules were developed by shifting either the ballast maintenance in year seven or the crosstie maintenance in year six so that they occur in the same year (Alternatives 1a, 1b, and 2 in Table 7.3). Performing the ballast maintenance early results in either the need to perform additional maintenance or an extended time between activities, so both options were evaluated (Alternatives 1a and 1b respectively). Using the methods outlined in this chapter, the total maintenance and disruption risk costs for the baseline maintenance plan and all alternatives were calculated (Figure 7.4, exact costs in Appendix H).

Table 7.3: x_{ij} for the base and alternative maintenance plans with adjusted years shaded in gray

Year (j)	Base maintenance plan			Alternative 1a			Alternative 1b			Alternative 2		
	Rail (R)	Crosstie (C)	Ballast (B)	R	C	B	R	C	B	R	C	B
0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	1	0	0	1	0	0	1	0	0	1
2	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	1	0	0	1	0	0	1	0	0	1
5	1	0	0	1	0	0	1	0	0	1	0	0
6	0	1	0	0	1	1	0	1	1	0	0	0
7	0	0	1	0	0	0	0	0	0	0	1	1
8	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	1	0	0	0	0	0	0

Comparing the results of all three options yields some common trends. One is that slow order and maintenance delay contribute most of the total cost. Using the more robust slow order delay models in Chapters 5 and 6 shows a slow order cost more in line with industry perceptions.

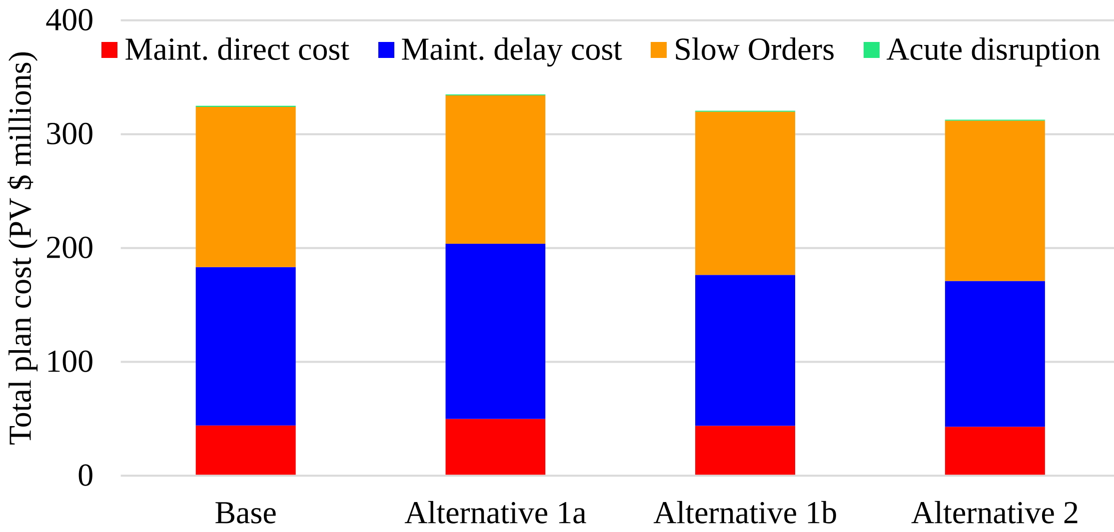

Figure 7.4: Comparison of maintenance plan alternative total costs

Acute disruption costs are much lower than previously found in Chapter 4 and other preliminary analysis (Lovett et al. 2015), but this is partly due to the decreased derailment rate in recent years (Association of American Railroads 2016b).

Comparing between the alternative maintenance schedules shows that Alternative 2 has the lowest total cost, while Alternative 1a has the highest. There is an approximately $20-million-dollar difference between Alternatives 1a and 2, largely due to the specific component that is being rescheduled. For Alternative 2, moving the crosstie renewal later in the planning period has almost no impact on the slow order or acute disruption costs, so the savings come from the economies of performing the crosstie and ballast maintenance in the same year. Moving the ballast maintenance one year earlier in Alternative 1a results in a $10 million slow order cost savings compared to the Base schedule but is offset by the additional ballast maintenance added in the last year of the planning period. If the additional ballast maintenance is not performed (Alternative 1b), the total plan cost is lower than the base plan but higher than Alternative 2 due to increased slow order costs at the end of the planning period.

This analysis shows the limitations of having a discrete maintenance planning horizon. If the maintenance planning period was extended far enough, the costs of subsequent maintenance activities would be explicitly included; however, it is unreasonable to extend the planning horizon indefinitely into the future. One way to compensate for a limited planning period is reevaluating the maintenance plan each year. The early parts of the planning period could be established, while the schedule in later years could be updated as they get closer to the present. This "rolling horizon approach" would also be beneficial in an optimization model since it reduces the number of years that need to be optimized, allowing for a faster solution time.

7.5 Conclusions and future work

This analysis shows an application of PRA in railroad track maintenance planning by considering the expected disruption costs with the maintenance costs. This approach can be used to determine if changes to regular component-specific maintenance schedules can be justified to reduce disruption costs or take advantage of combining activities. The case study presented here shows the importance of considering all costs that might be affected by maintenance timing. For example, performing maintenance early will reduce the disruption costs but might increase the number of maintenance activities being performed in the planning period. If all of the costs were not included in the analysis, the extra ballast maintenance or additional disruption risk may not have been properly accounted for. A rolling horizon planning approach could compensate for this.

To improve the risk analysis approach presented here, advances need to be made in two areas. First, there are other benefits of combining maintenance activities as will be further discussed in Chapter 8. Including these additional benefits would more accurately compare disruption risk with maintenance economies when developing maintenance plans.

Second, to fully implement PRA in a maintenance-planning framework, a large amount of data are required. This includes the occurrence of slow orders and derailments, capital maintenance timing, the number of trains affected by disruptions, train delay amounts and causes, inspection equipment reliability, and so forth. Much of these data are recorded by the major railroads, but it must be integrated and analyzed to determine the probability and cost of a train being delayed by a slow order, acute disruption, or cascading delay. Once these probability distributions have been established, the range of expected costs can be established and used for maintenance planning. As new data become available, it can be used to update the probability distributions for further analysis. Even if the analysis is limited to the simplified annual risk method described in this chapter, additional data could be applied to developing better component degradation models and improve the accuracy of the risk analysis. Whether the simplified or more detailed approach is used, including the risk of disruptions in maintenance planning can be a powerful tool in understanding the complete cost of operating and maintaining a railroad.

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CHAPTER 8.

AGGREGATING RAILROAD TRACK MAINTENANCE ON EXTENDED WORK WINDOWS

8.1 Introduction

A relatively recent development in North American railroad track maintenance is to aggregate maintenance activities on extended work windows, although a form of this practice has been used in Europe for much longer (Burns 1980). Sometimes referred to as a “blitz” or “jamboree,” this method consists of removing a line from service for several days and performing maintenance on multiple parts of the track. CSX and BNSF have been performing maintenance jamborees or blitzes since 1999 (Dischinger 1999; Railway Track & Structures 2015) while Union Pacific has been using elongated work windows since 1996 (Ingles 1996). This practice differs from traditional track maintenance where components are maintained on separate schedules in multiple short work windows. While the traditional method relieves congestion by allowing trains to resume operations between maintenance windows, it reduces maintenance efficiency because crews spend considerable time waiting for trains to pass, then setting up equipment only to have to remove it again before the work window ends. Conversely, extended track outages are more disruptive to train operations because of additional costs associated with substantially delaying, rerouting, or canceling trains (Burns & Franke 2005a, 2005b).

The aggregated method requires removing the track from service for an extended period, either in 24-hour blocks or continuously for several days, and allowing multiple crews to work on several parts of the track and related infrastructure. Aggregating maintenance in this fashion can improve productivity and efficiency by avoiding duplicate maintenance activities and reducing the number of times equipment must be set up, the total amount of track time required, and the frequency of outages.

When planning track maintenance, selecting the proper level of maintenance aggregation is a complex economic and engineering decision. Consideration and quantification of the direct and indirect costs of track ownership will allow for a better understanding of how maintenance scheduling will influence total costs. Deferred maintenance, which may occur when aggregating, relates to the DCF Trap discussed in Chapter 1. Modifying the risk analysis model in Chapter 7 to consider the benefits of aggregation allows for the costs of maintenance deferral to be quantified and compared against the benefits from aggregation.

8.2 Literature review

Previous work has considered various aspects of maintenance aggregation, but little has been done in the rail industry specifically. Burns & Franke (2005a) quantified the efficiency of longer work windows; however, they assumed that work would be performed on all aspects of the track rather than analyze specific combinations of individual activities and the possible resultant efficiencies. For this paper, these will be termed the economies of aggregation and include the cost reductions that come from aggregating maintenance or using elongated work windows. Other research has considered aggregating maintenance on lines that are out of service because shipper traffic has been temporarily suspended, so operational issues can be disregarded (Martland 2008; Peng 2011). Santos et al. (2015) evaluated schedule adjustments, and Zhao et al. (2009) examined maintenance aggregation, but neither considered the effects on disruption risk. There are also railroad specific models that plan maintenance for traditional execution (Higgins 1998; Higgins et al. 1999; Peng et al. 2011).

More research has been performed in the factory domain and other systems that have high downtime costs that are similar to the railroad in many respects. Cho & Parlar (1991) reviewed several models for maintaining “multi-unit systems.” One model they evaluated specifically looked at systems where the failure of a single component would cause the entire system to fail. This is similar to railroad track since a component failure will cause trains to either stop running or proceed at reduced speed. For railroads, component failure would generally require the failure of several component units, such as a group of crossties since there are redundancies built into the track support structure. Another model Cho & Parlar (1991) reviewed evaluates the impact of maintaining components out of cycle because the system has already been shut down to work on another component. The resultant efficiencies can be directly applied in combining maintenance on track that must be taken out of service for maintenance.

Maillart & Fang (2006) developed a model that includes both system availability and maintenance cost. Their model evaluates units in series rather than in parallel, which would be the case when analyzing a series of railroad track sections rather than components in a given track segment. Peng et al. (2011) considered this approach, but it is a different concept than combining different types of maintenance at the same location. The model developed by Yao et al. (2004) corresponds particularly well with the maintenance aggregation situation. It considers the higher cost of unplanned downtime, modification of a general maintenance schedule to correspond with other maintenance, and lost production. All of which need to be considered in railroad maintenance as well.

Wildeman et al. (1997) evaluated grouping maintenance activities that have the same setup cost. Setup costs are defined to include both actual setup costs and the costs of taking the system out of service. For track maintenance, this could be a reasonable assumption when considering train delay costs, which will be the same on a train-hour basis no matter what activity is performed. In contrast, the actual costs to set up the equipment will not be the same and will still need to be considered if multiple maintenance activities are performed at the same time. Another aspect of this model that could be beneficial for application in railroad track maintenance is the penalty functions that are applied to activities shifted from the optimal schedule. These penalty costs are associated with degradation of the system, so it is possible that the penalty cost will be negative if the maintenance is performed early. This penalty cost could be analogous to disruption risk, which could be determined for a given operating condition.

Wildeman et al. (1997) also discuss the benefits of combining activities associated with reducing duplicated efforts, but there will be other effects if the schedule is adjusted. In the case of railroad track maintenance, tamping, fastener removal, and flaggers are needed for multiple activities and would only be needed once when maintenance is aggregated. Maintenance such as tamping and rail grinding can shorten the component's useful life if done prematurely, so that should also be considered if sufficient data are available. Aggregating track maintenance activities will also reduce the amount of track time required because work can be overlapped and longer work windows will decrease the number of equipment setups required.

Although many of these approaches have aspects that can be applied to include the economies of aggregation in maintenance planning, there are opportunities for improvement. Factory maintenance models consider the impact of shutting the system down, but railroads have added complexity during service disruptions in the form of slow orders and possible rerouting. Rerouting is more common with elongated work windows to mitigate traffic disruptions. The rail models that consider schedule adjustments do not to adequately account for disruption costs or reroutes. The costing model in Chapter 7 includes disruption risk, so applying the aggregation principles from factory maintenance and other rail research will improve on the existing models and provide a well-rounded framework for maintenance planning.

8.3 Methodology

To allow the risk-based maintenance planning model to consider the economies of aggregation, there needs to be some modification to the formulation of the maintenance related costs from Chapter 7 but will follow the basic form (Equation 8.1). Disruption costs associated with slow orders and acute disruptions will remain the same.

$$C_{Total} = \sum_{j} \left(\frac{1}{(1+R_I)^j} \left(C_{Mj} + C_{DMj} + C_{SOj} + C_{Xj} \right) \right) \qquad 8.1$$

Where:

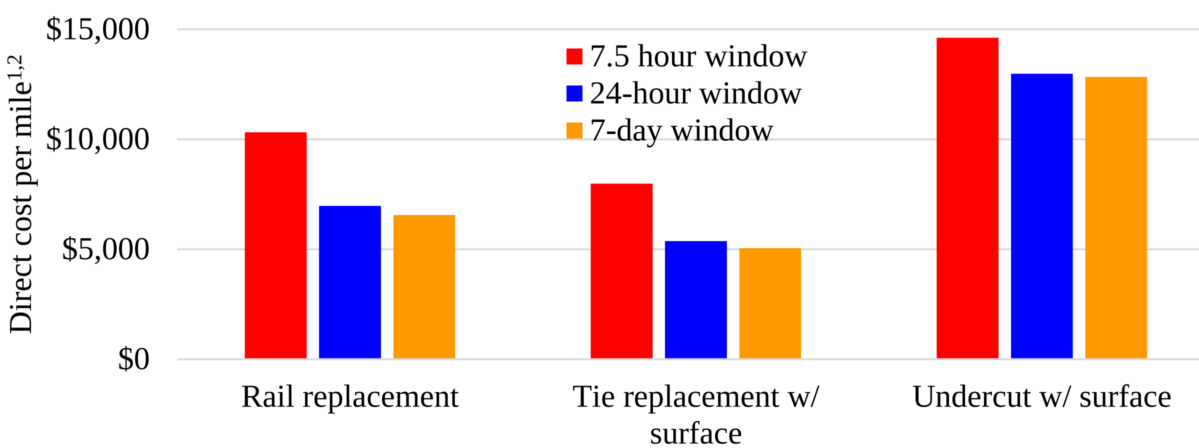
- C_{Total} – total cost associated with the track performance during the planning period
- j – set of years in the analysis period
- R_I – discount rate
- C_{Mj} – cost to perform maintenance in year j
- C_{DMj} – cost of delay due to maintenance activities in year j
- C_{SOj} – slow order cost in year j
- C_{Xj} – average acute disruption cost in year j

8.3.1 Maintenance costs

Direct maintenance costs consist of the labor, equipment, and materials necessary to perform a maintenance activity. They may also be affected by economies of aggregation and therefore vary based on the window length and level of aggregation. Burns & Franke (2005a) used typical labor and equipment costs for a variety of work window lengths. When maintenance is not aggregated, their rail, crosstie, and undercutting values from the 7.5-hour work windows were used. When maintenance was aggregated, 7-day or discrete 24-hour windows were used if a detour was available or not, respectively.

As material costs would not be affected by the window length, Burns & Franke (2005a) did not consider them; however, since advancing or deferring maintenance may change the number of times maintenance is performed, material costs are needed. Material costs were gathered from several sources (Chrismer 1988; Burns 1989; ACW Railway Company 2015). The Burns & Franke (2005a) values for crosstie replacement and undercutting time and costs were modified to reflect that tamping is required after completion (Hay 1982). These adjustments are described in more detail in Chapter 7 and are detailed in Appendix I.

The direct cost savings (Figure 8.1) can be attributed to increased time efficiency because less time is spent mobilizing and demobilizing crews and equipment. This is despite the fact that longer windows require more breaks and have lower labor efficiency (Burns & Franke 2005b). Aggregation can provide additional benefits, from the reduction of procedures that are required for multiple activities, including surfacing after crosstie renewal and undercutting, flaggers, and taking track out of service. The flagger cost is included in the maintenance costs and is relatively small, so it will not be addressed explicitly here. These additional savings would seem to imply



1. Materials costs not included
2. 1 mile = 1.6 km

Figure 8.1: Direct costs for various work windows lengths (Burns & Franke 2005b)

that longer work windows are always better, but the direct costs of a single maintenance event do not consider the impact of train delay or long-term impacts of consolidating activities, which will both be addressed later in this chapter. Accounting for the varied costs and potential savings associated with maintenance aggregation requires some modification from the formulation in Chapter 7 (Equation 8.2).

$$C_{Mj} = L_R \left(\sum_{w} a_{jw} \left(\sum_{i} x_{ij} C_{Jiw} - x_{Crosstie,j} x_{Ballast,j} C_{Sw} \right) \right) \qquad 8.2$$

Where:

- L_R – route length
- w – set of aggregation options, {1 = 7.5 hours, 2 = 24 hours, 3 = 7 days}
- a_{jw} – binary indicator for if aggregation on window type w in year j
- i – index for track components, {Rail, Crossties, Ballast}
- x_{ij} – binary indicator for maintenance being performed on component i in year j
- C_{Jiw} – direct cost per mile (1.6 km) to perform maintenance on component i on window type w
- C_{Sw} – direct cost per mile (1.6 km) to surface the track on window type w

Other variables as previously defined

8.3.2 Train delay

Train delay costs occur because a section of track must be taken out of service for maintenance to be performed. In Chapter 7, the delay costs associated with a maintenance activity were limited to stopping trains, but as mentioned above, there is also the possibility of detours (Burns & Franke 2005b). If a detour is available, then additional cost categories must be considered. In addition to the delay associated with rerouting, which is likely to be longer than the original route, there will also be planning and access costs. The planning costs are taken as a fixed value to negotiate and schedule the detour. Access costs include the cost of an additional crew member who is certified on the territory and a per ton-mile fee (Burns & Franke 2005b). Based on industry input, the ton-mile fee, or millage, value used may be low, but it is the only published value I have been able to find. Train delay costs are only applied to the additional time it takes the trains to traverse the detour as compared to the normal route. If a route has two parallel tracks, the second track can act as a detour with zero additional length. As shown by the parametric models used in Chapter 4, there will be additional delay when part of the double track is removed.

As in Chapter 7, the methodology from Chapter 5 will be used to account for the effects of both traffic stopping and associated slow orders. The new formulation will include considerations for the different window lengths and the possibility of detours (Equation 8.3 – 8.6). This formulation assumes that maintenance will not be aggregated or detoured when normal, 7.5-hour, work windows are used. Since all activities that are aggregated on long work windows will be performed at the same time, there is no need to remove the delay associated with surfacing, except when normal work windows are used. As discussed in Chapter 5, maintenance activities that disrupt the track structure, such as crosstie and ballast work, require a "seasoning" period to stabilize the track support (Selig & Waters 1994). When a detour is used, the delay incurred during the seasoning period must be explicitly included since it will not be included in the detour costs.

$$C_{DMj} = L_R\left(a_{j1}C_D\left(1-b_j\right)\left(\sum_i x_{ij}T_{DMJij}Q_{J,i,1} - x_{Crosstie,j}x_{Ballast,j}Q_{S,1}T_{DSj}\right) + Q_{Wj}\left(1-a_{j,1}\right)\left(C_D\left(1-b_j\right)\left(T_{Mj}\right) + b_j\left(C_{Lj}+C_DT_{BMj}\right)\right)\right) \quad 8.3$$

$$Q_{Wj} = \begin{cases} \sum_w a_{jw} Q_{J,Rail,w}, & a_{j,1} = 0, x_{Rail,j} = 1 \\ \sum_w a_{jw} Q_{J,Crosstie,w}, & a_{j1} = 0, x_{Rail,j} = 0, x_{Crosstie,j} = 1 \\ \sum_w \left(\sum_i x_{ij} a_{jw} Q_{Jiw} - x_{Crosstie,j} x_{Ballast,j} Q_{Sw} \right), & else \end{cases} \quad 8.4$$

$$C_{Lj} = C_P + L_L \left(C_T \frac{N_{Aj} \times 1{,}000{,}000}{365 \times 24} T_{Mj} + \frac{C_K}{V_L} \right) + C_D \left(\frac{L_L}{V_L} - \frac{L_R}{V_N} \right) \quad 8.5$$

$$T_{Mj} = \sum_w a_{jw} T_{Mw} \quad 8.6$$

Where:

C_D – train delay cost ($ per train-hour)
T_{DMji} – train delay per window for component i in year j from Chapter 5
Q_{Jiw} – number of work windows per mile (1.6 km) required to maintain component i
Q_{Sw} – number of work windows required to surface the track on window type w
T_{DSj} – surfacing train delay per window in year j from Chapter 5 on a normal work window
Q_{Wj} – total number of work windows per mile (1.6 km) required to complete all activities in year j
b_j – binary indicator for if a detour was selected for use in year j
T_{Mj} – train delay per window for in year j based on the selected maintenance activities and aggregation
C_{Lj} – detour cost per window in year j
T_{BMj} – post maintenance seasoning train delay per window in year j based on the selected maintenance activities and aggregation when a detour is used
C_P – detour planning cost
L_L – detour length
C_T – millage
N_{Aj} – annual tonnage in year j (MGT)
T_{Mj} – work window length selected in year j
C_K – hourly cost of an additional crewmember
V_L – detour operating speed
V_N – normal route operating speed
T_{Mw} – work window length for window w
Other variables as previously defined

8.4 Schedule modification

As mentioned above, aggregating track maintenance requires adjusting the schedules of individual maintenance activities so they will occur at the same time. This was discussed briefly in Chapter 7 and will be expanded here. Adjusting maintenance schedules will have both positive and negative impacts on the costs of track ownership. If maintenance is performed early, the entire useful life of the component may not be realized and maintenance might be performed more times in the planning period. In contrast to this, the disruption risk on the track segment may decrease because of the improved track condition. If maintenance is deferred, the disruption risk and need for spot maintenance will increase, but overall maintenance frequency and expense will decrease. The loss in useful life is difficult to quantify based on how railroads depreciate their track components (Surface Transportation Board 2014). Since components that are removed from service while they are still useful can be cascaded to lower priority tracks, the value is not completely lost (Hay 1982). As mentioned above, the potential negative effects of tamping and rail grinding should be included to the extent possible. Because of these various pros and cons to schedule modification, it was necessary to consider multiple modification strategies for comparison to the traditional maintenance schedule.

Five maintenance-scheduling procedures were identified to see the general effects of aggregation and elongated work windows. The first is based on traditional maintenance practices and has normal window length and no aggregation. The first aggregation method does not consider schedule modification, and only activities that are already scheduled to occur in the same year are combined, which shows the effect of aggregation without schedule modification. The remaining three procedures shifted activities within a three-year period (Figure 8.2). When multiple activities are scheduled to occur within the period, they are aggregated in the year of the first activity, the last activity, or in the middle year. This will help show the impacts of advancing versus deferring maintenance when compared to the benefits of aggregation. For both the first- and last-year methods, a cascading effect can be observed where each schedule adjustment is

	Traditional			First Year			Middle year			Last Year		
Year	Rail	Crosstie	Ballast	Rail	Crosstie	Ballast	Rail	Crosstie	Ballast	Rail	Crosstie	Ballast
0	R	T	B	R	T	B	R	T	B	R	T	B
1												
2												
3			B			B			B			B
4												
5												
6			B		T	B						
7								T	B			
8		T									T	B
9			B			B						
10									B			
11												B
12			B		T	B						
13												
14								T	B			
15			B			B						
16		T									T	B
17									B			
18			B	R	T	B						
19												
20	R									R		B

Figure 8.2: Effect of schedule modification process

compounded for subsequent activities. This occurs in an attempt to maintain the original schedule when possible since non-adjusted activities would ideally keep their original maintenance cycle.

8.5 Case study

The costing model was applied to a case study with a 50-year planning period for each of the five scheduling methods using the assumed parameters (Table 8.1). Although maintenance planning would not typically take place over a 50-year horizon, the long period allows for a better perspective on the effects of aggregation on long work windows.

Table 8.1: Select case study parameters

Factor	Value
Planning period	50 years
Discount rate	9.61%[1]
Route length	100 miles[2]
Route and detour speed limit	40 mph[2]
Annual Tonnage	30 MGT
Trains per day	12
Train delay cost	$950 per train-hour[3]
Millage	$0.002 per ton-mile[2,4]
Detour additional cost	$2,000 per detour[4]
Additional distance due to detour	100 miles[2]

1. (Surface Transportation Board 2016)
2. 1 mile = 1.6 km
3. From Chapter 3
4. (Burns & Franke 2005b)

The results of the case study indicated that aggregation with extended work windows can provide long-term cost savings whether a detour is available or not (Figure 8.3, detailed values

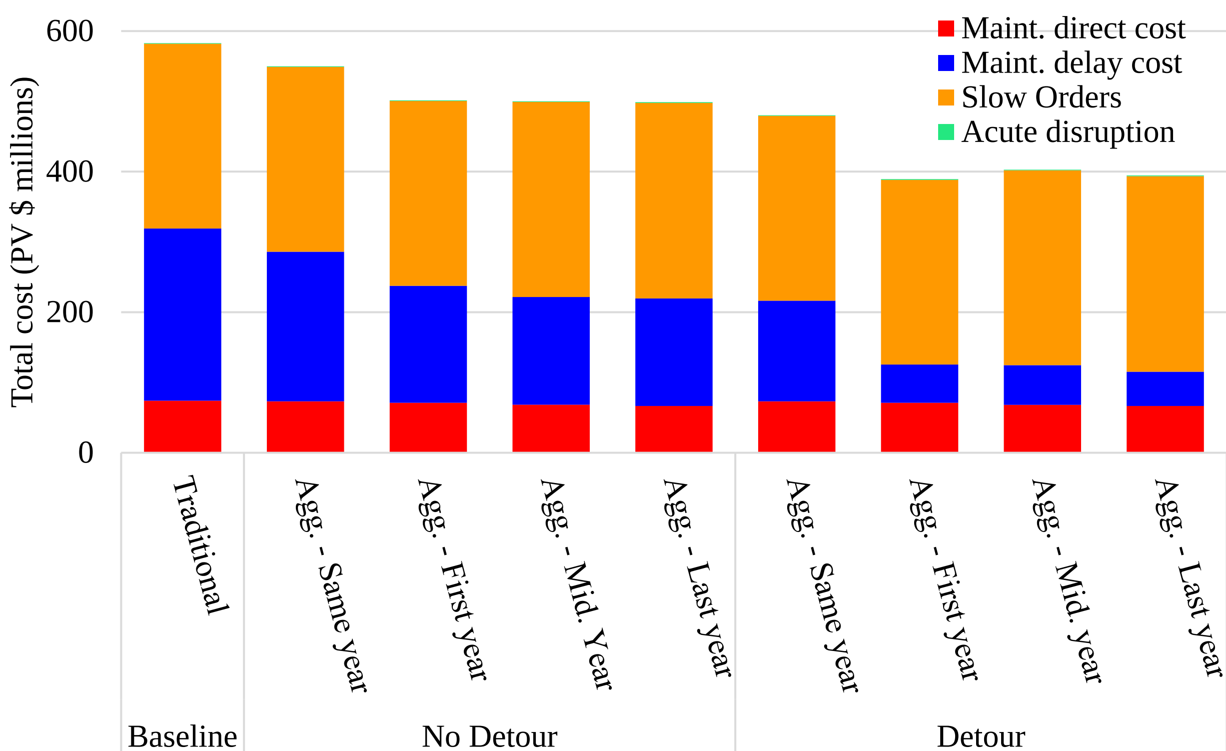


Figure 8.3: Present value of 50-year life cycle cost

are given in Appendix J). While there are minor direct maintenance cost savings from aggregation, the main benefits come from maintenance related delay costs. These benefits are particularly noticeable when a detour is available and occur because maintenance is being performed more efficiently and requires less overall track time. The availability of detours reduces the delay costs during the maintenance outage and removes the cascading delay except when associated with the post-maintenance-seasoning period.

Allowing for schedule modification further reduces costs because there are more opportunities for aggregation. When comparing between the schedule modification alternatives, aggregating maintenance in the first-year results in the lowest costs. These savings are due to the reduction in slow order costs because maintenance is being performed earlier. When maintenance is deferred for aggregation, the disruption costs increase slightly, but there is a reduction in maintenance related costs because the expenditures occur later. Aggregating to a middle year results in a slightly higher cost than the last year aggregation. While it is not obvious why this occurs, it is likely due to how the schedule adjustments take place. The middle-year aggregation results in more incidents of maintenance being performed without the substantial disruption cost savings associated with the first-year aggregation method.

In contrast to the analysis in Chapter 4, slow orders are a dominant cost component, while acute disruptions are extremely small. This is partly due to the improved slow order impact model from Chapter 5. The reduction in acute disruption costs is likely due to the decreased derailment rate that has been observed over recent years and the more detailed derailment rates used (Association of American Railroads 2016a, 2016b; Liu et al. 2017).

8.6 Conclusions and Future work

This chapter enhanced the risk-based maintenance-costing model presented in Chapter 7 by including maintenance aggregation and detours. Several maintenance schedules with varying aggregation methodologies were evaluated using the cost model and found that the deciding factor in the least-cost-scheduling regimen is train delay, although maintenance aggregation alone can reduce the overall cost of a maintenance plan. Specific circumstances will dictate the optimal maintenance regimen, but this analysis indicates that when aggregation is used, maintenance activities should be rescheduled to the earliest year.

One key area of future research will focus on optimizing the maintenance schedule using the risk-based cost model and will be discussed in Chapter 9. Other work can be done to expand the applicability of the model that is beyond the scope of this dissertation. It would include gathering improved data on the costs to perform maintenance for different components, levels of aggregation, and work window lengths. This will provide a better understanding of the costs and benefits of performing maintenance under different circumstances and when schedule modification is most applicable. As mentioned in other chapters, improving the disruption risk models will provide better estimates and give a better understanding of the effects of schedule adjustments.

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CHAPTER 9.

MULTI-ROUTE TRACK MAINTENANCE PLANNING OPTIMIZATION MODEL USING SIMULATED ANNEALING

9.1 Introduction

In this chapter, I develop an optimization model for multi-route track maintenance planning using the risk-based model developed in previous chapters. As discussed throughout this dissertation, the evaluation of a track maintenance plan requires consideration of both direct and indirect costs, and this extends to its optimization. Understanding how and when track-related service disruptions are expected to occur can help ensure proper timing of capital maintenance. This is related to the DCF-trap concept in which increased disruption risks due to further track degradation need to be balanced against the potential benefits of delaying maintenance expense (See Chapters 1 and 8). The model optimizes the timing, level of maintenance aggregation, and detours for multiple track segments over a multi-year planning period. In optimizing the maintenance plan for a network, the scope should also include maintenance equipment routing costs to ensure that resources are effectively utilized (See Chapter 2). The model presented here uses a simplified equipment routing cost approach to demonstrate how resource utilization could be considered. Since the model is complex and highly non-linear, a metaheuristic was applied to find a near optimal solution.

9.2 Optimization model formulation

The multi-route track maintenance planning optimization model follows the general forms introduced in Chapters 7 and 8. Total cost during the planning period as calculated by the objective function (Equation 9.1 – 9.2) is minimized subject to a budget constraint (Equation 9.4), equipment utilization constraint (Equation 9.5), and binary selection constraint (Equation

9.6). The model formulation considers multiple routes and includes equipment routing costs (Equation 9.3). Model indices (Table 9.1), decision variables (Table 9.2), inputs (Table 9.3), and intermediate calculated parameters (Table 9.4) are largely the same as in Chapters 7 and 8 with modifications for double track and multiple routes. When the model is solved, the minimum-cost maintenance plan is described by the binary decision variables x_{ijk}, a_{jkw}, and b_{jk} indicating the track component maintenance activities to conduct, type of aggregation, and whether a detour is used on each route during each year of the planning period.

$$\min C_{Total} \quad \text{s.t.} \tag{9.1}$$

$$C_{Total} = \sum_j \left(\frac{1}{(1+r)^j} \left(C_{Gj} + \sum_k C_{Mjk} + C_{SOjk} + C_{Xjk} + C_{DMjk} \right) \right) \tag{9.2}$$

$$C_{Gj} = C'_{Gj} \sum_{i,k} x_{ijk}\,, \qquad \forall j \tag{9.3}$$

$$C_{Budgetj} \geq C_{Gj} + \sum_k C_{Mjk}\,, \quad \forall j \tag{9.4}$$

$$N_{Eij} \geq \sum_k x_{ijk}\,, \qquad \forall i, j \tag{9.5}$$

$$1 \geq \sum_w a_{jkw}\,, \qquad \forall j, k \tag{9.6}$$

Table 9.1: Model indices

Index	Definition
i	Index for track components, {Rail, Crossties, Ballast}
j	Set of years in the analysis period
k	Set of routes being planned
w	Set of window length options, {1 = 7.5 hours, 2 = 24 hours, 3 = 7 days}

Table 9.2: Model decision variables

Variable	Definition
x_{ijk}	Binary indicator for maintenance being performed on component *i* in year *j* on route *k*
a_{jkw}	Binary indicator for if aggregation on window type *w* in year *j* on route *k*
b_{jk}	Binary indicator for if a detour was selected for use in year *j* on route *k*

Table 9.3: Model input parameters

Parameter	Definition
C'_{Gj}	Average cost to transport equipment between maintenance activities in year *j*
C_{BM}	Direct cost to repair a rail break
$C_{Budgetj}$	Direct maintenance budget in year *j*
C_{Djk}	Train delay cost in year *j* on route *k*
C_{Jiw}	Direct cost per mile to perform maintenance on component *i* on window type *w*
C_{Kjk}	Hourly cost of an additional crew member in year *j* on route *k*
C_P	Detour planning cost
C_{SODi}	Direct cost to correct a slow order causing a defect in component *i*
C_{Sw}	Direct cost per mile to surface the track on window type *w*
C_{Tjk}	Millage in year *j* for route *k* ($ per ton-mile[1])
$C_{XD,Rail}$	Average broken-rail-caused derailment cost
C_{Xli}	Average derailment cost due to component *i* in track class l
d_{jk}	Binary indicator for if route *k* has two mainline tracks
L_{Ljk}	Detour length in year *j* on route *k*
L_{Rjk}	Route length in year *j* on route *k*
L_{SO}	Length of an individual slow order
N_{Ajk}	Annual tonnage in year *j* on route *k* (million gross tons (MGT))
N_{Eij}	Number of jobs equipment for maintenance type *i* can accomplish in year *j*
N_{Rail}	Number of rail sections per mile[1]
$P_{X,Rail}$	Probability of a derailment given a rail break
P_{Xli}	Proportion of derailments on track class *l* caused by component *i*
Q_{Miw}	Number of work windows per mile[1] required to maintain component *i* on window type *w*
Q_{Sw}	Number of work windows required to surface the track on window type *w*
r	Discount rate
R_{Xl}	Derailment rate on track class *l* (billion gross ton-miles[1])
S_1	Single-track delay (19.5206[2])
S_2	Delay mitigation constant (19.149[2])
T_{DMJ2jk}	Double-track delay on route *k* in year *j*
T_{Eik}	Average length of time a slow order due to component *i* is left in place on route *k*
T_{Iijk}	Inspection interval for component *i* in year *j* on route *k*
U	Congestion factor (0.0471 (Sogin et al. 2016))
V_{Ljk}	Detour operating speed in year *j* on route *k*
V_{Njk}	Normal route operating speed in year *j* on route *k*
$y_{Rail,jk}$	Years since rail replacement in year *j* on route *k*
α_{Rail}	Weibull shape factor
β_{Rail}	Weibull scale factor
ΔN_{jk}	Average tonnage between rail inspections in year *j* on route *k* (MGT)
θ	Minimum inspection interval
λ	Orringer model proportionality factor

1. 1 mile = 1.6 km
2. (Sogin et al. 2016)

Table 9.4: Model calculated parameters

Parameter	Definition
C_{DMjk}	Cost of delay due to maintenance activities in year *j* on route *k*
C_{Gj}	Equipment routing costs in year *j*
C_{Ljk}	Detour cost per window in year *j* on route *k*
C_{Mjk}	Cost to perform maintenance in year *j* on route *k*
C_{SOjk}	Slow order cost in year *j* on route *k*
C_{Total}	Total cost associated with the track performance during the planning period
C_{Xjk}	Average acute disruption cost in year *j* on route k
P_{SOijk}	Proportion of the track slow ordered during year *j* on route k
Q_{Ejk}	Total number of work windows per mile[1] required to complete all activities in year *j* on route *k*
R_{Bjk}	Annual rail break rate per mile[1] in year *j* on route k
R_{SOijk}	Slow order rate per mile[1]-year according to the models in Chapter 6 for component *i* in year *j* on route *k*
T_{BMjk}	Post-maintenance seasoning train delay per window in year *j* on route *k* based on the selected maintenance activities and aggregation when a detour is used
T_{DBjk}	Train delay due to a rail break in year *j* on route *k* based on Chapter 5
T_{DMJ2jk}	Double-track delay on route *k* in year *j*
T_{DMjik}	Train delay per window for component *i* in year *j* on route *k* from Chapter 5
T_{DSjk}	Surfacing train delay per window in year *j* from Chapter 5 on a normal work window
T_{DSOij}	Train delay based on Chapter 5 with parameters associated with this line
T_{DXjk}	Train delay costs due to a derailment in year *j* on route *k* based on Chapter 5
T_{Mjk}	Work window length selected in year *j* on route *k*
T_{Mw}	Work window length for window *w*

1. 1 mile = 1.6 km

The formulation enhances the model described in Chapter 8 by considering multiple segments in a network. Since maintenance is typically planned and performed over a network rather than a single line, this model calculates the cost of the maintenance plan for multiple lines subject to an overall network budget. Another enhancement is the inclusion of maintenance equipment routing costs to reach each project site. Rather than develop a complex routing model that requires a detailed network with exact travel distances, an average equipment routing cost per deployment (project) is used. As discussed in Chapter 2, incorporating both degradation and routing is necessary to fully quantify the costs of a maintenance plan. The use of a simplified model helps demonstrate how equipment routing costs can be incorporated once a satisfactory one has been developed or identified.

The direct maintenance cost calculation (Equation 9.7) has the same general form as presented in Chapter 8, except a new factor is included to multiply the cost by two if there are two mainline tracks on a route. This factor does not apply to passing sidings, as they typically have lower maximum allowable speeds and correspondingly less capital maintenance requirements than the main track.

$$C_{Mjk} = L_{Rjk}(1 + d_{jk}) \sum_{w} a_{jkw} \left(\sum_{i} x_{ijk} C_{Jiw} - x_{Crosstie,jk} x_{Ballast,jk} C_{Sw} \right), \forall j, k \qquad 9.7$$

Disruption costs (Equations 9.8 – 9.11) have the same general form as in Chapters 7 and 8 but the equations were modified to include a multiplier for a second main track. Equation 9.8 calculates direct and delay costs associated with slow orders. The crosstie slow order probability from Chapter 6 was modified slightly to consider the exact maintenance timing determined by the algorithm rather than assume the standard renewal interval. Equation 9.9 calculates acute disruption costs. Equation 9.10 calculates the number of rail breaks for determining rail-caused acute disruptions. Equation 9.11 calculates the proportion of the track that is operated at a lower track class for determining crosstie- and ballast-caused acute disruptions. This formulation assumes that routes with two mainline tracks have evenly-distributed, directional traffic, and trains are not diverted to the other main track when a slow order is in place. During an acute disruption, it is assumed that both tracks are removed from service to ensure that repairs can be made as quickly and safely as possible. Thus, a slow order only affects trains operating in one direction while an acute disruption impacts all trains on a route.

$$C_{SOjk} = (1 + d_{jk}) \sum_{i} \left(L_{Rjk} R_{SOijk} C_{SODi} + \frac{C_{Djk} T_{DSOijk}}{T_{Iijk}} \right), \qquad \forall j, k \tag{9.8}$$

$$\begin{aligned} C_{Xjk} = L_{Rjk}(1 + d_{jk}) \Bigg(& R_{Bjk} \left((C_{BM} + C_{Djk} T_{DBjk}) + P_{XRail}(C_{XD,Rail} + C_{Djk} T_{DXjk}) \right) \\ & + \frac{N_{Ajk}}{1000} \sum_{i \neq Rail} P_{SOijk} C_{X(l-1)i} R_{X(l-1)} P_{X(l-1)i} \\ & + (1 - P_{SOijk}) C_{Xli} R_{Xl} P_{Xli} \Bigg), \forall j, k \end{aligned} \tag{9.9}$$

$$R_{Bjk} = N_{Rail} \lambda(\Delta N_{jk} - \theta) \frac{\left(e^{-\left(\frac{N_{Ajk} y_{Rail,jk}}{\beta_{Rail}}\right)^{\alpha_{Rail}}} - e^{-\left(\frac{N_{A,jk}(y_{Rail,jk}+1)}{\beta_{Rail}}\right)^{\alpha_{Rail}}} \right)}{1 + \lambda(\Delta N_{jk} - \theta)}, \qquad \forall j, k \tag{9.10}$$

$$P_{SOijk} = \min(L_{SO} R_{SOijk} T_{Eik}, 1), \qquad \forall i, j, k \tag{9.11}$$

The maintenance delay cost calculation (Equations 9.12 – 9.17) is modified from previous chapters to account for differences in delay between single and double track. Equation 9.12 calculates maintenance-caused train delay for independent activities, aggregation, and detours, for both single and double track. Equation 9.13 calculates the number of work windows required to complete the planned maintenance based on the level of aggregation and planned activities. Equation 9.14 calculates the detour related costs. Equation 9.15 calculates the work window length based on the values of a_{ijw}. When a detour is not used, the parametric-delay model from Chapter 4 is used to determine the double-track delay (Sogin et al. 2016), and the model from Chapter 5 estimates the post-maintenance slow order delay (Equation 9.16). If a detour is used on a double-track line, the detour model from Chapter 8 is used, but the effects of the post-maintenance slow order will be doubled because both tracks will not be maintained at the same time.

$$
\begin{aligned}
C_{DMjk} = L_{Rjk} \Bigg(& a_{jk1} C_{Djk} (1 - b_{jk}) \\
& \times \left((1 - d_{jk}) \left(\sum_i x_{ijk} Q_{M,i,1} T_{DMJijk} - x_{Crosstie,jk} x_{Ballast,jk} Q_{S,1} T_{DSjk} \right) \right. \\
& \left. + Q_{Ejk} d_{jk} T_{DMJ2jk} \right) \\
& + Q_{Ejk} (1 - a_{jk,1}) \Big(C_{Djk} (1 - b_{jk}) \big((1 - d_{jk}) T_{DMjk} + d_{jk} T_{DMJ2jk} \big) \\
& + b_{jk} \big(C_{Ljk} + C_{Djk} (1 + d_{jk}) T_{BMjk} \big) \Big) \Bigg), \qquad \forall j, k
\end{aligned}
\tag{9.12}
$$

$$
Q_{Ejk} = \begin{cases} \sum_w a_{jkw} Q_{M,Rail,w}, & a_{jk,1} = 0, x_{Rail,jk} = 1 \\ \sum_w a_{jkw} Q_{M,Crosstie,w}, & a_{jk1} = 0, x_{Rail,jk} = 0, x_{Crosstie,jk} = 1 \\ \sum_w \left(\sum_i x_{ijk} a_{jkw} Q_{Miw} - x_{Crosstie,jk} x_{Ballast,jk} Q_{Sw} \right), & else \end{cases}, \qquad \forall j, k \tag{9.13}
$$

$$
C_{Ljk} = C_P + L_{Ljk} \left(C_{Tjk} \frac{N_{Ajk} \times 1{,}000{,}000}{365 \times 24} T_{Mjk} + \frac{C_{Kjk}}{V_{Ljk}} \right) + C_{Djk} \left(\frac{L_{Ljk}}{V_{Ljk}} - \frac{L_{Rjk}}{V_{Njk}} \right), \forall j, k \tag{9.14}
$$

$$
T_{Mjk} = \sum_w a_{jkw} T_{Mw}, \qquad \forall j, k \tag{9.15}
$$

$$
\begin{aligned}
T_{DMJ2jk} = (1 + d_{jk}) \Bigg(& \frac{T_{Mjk} N_{Njk} L_{Rjk}}{240 \times 60} \left(S_1 - S_2 \frac{(L_{Rjk} - L_{Mjk})}{L_{Rjk}} \right) e^{24U \times N_{Njk}} \\
& + \begin{cases} T_{DSjk}, & x_{Crosstie,jk} + x_{Ballast,jk} > 0 \\ 0, & else \end{cases} \Bigg), \qquad \forall j, k
\end{aligned}
\tag{9.16}
$$

9.3 Solution techniques

The multi-route maintenance planning optimization model detailed in the previous section includes the time value of money and a number of non-linear sub-modules. Additionally, the sub-modules for calculating train delay and slow order risk are complex with layers of equations. Due to these factors, the model cannot be solved using linear methods and a metaheuristic is developed.

Metaheuristics "orchestrate an interaction between local improvement procedures and higher-level strategies to create a process capable of escaping from local optima and performing a robust search of a solution space" (Gendreau & Potvin 2010a). This is done by making minor changes to an initial solution and exploring some sub-optimal intermediate results with the understanding that they might lead to the true optimum. While metaheuristics do not guarantee a globally optimal solution, they provide a way to improve an initial feasible solution for complex problems that cannot be solved using exact methods (Hillier & Lieberman 2015).

For the track maintenance planning problem, the initial feasible solution is a base maintenance plan. A metaheuristic makes modifications to maintenance timing, level of aggregation, and detour use to see if different combinations reduce the total cost of the maintenance plan. As shown in Chapter 8, it is not always obvious if it is better to advance or defer maintenance to take advantage of aggregation. Using a metaheuristic can allow exploration of both options. There are several common metaheuristics that are potential solution approaches for the track maintenance planning problem. The following sections introduce three of the most popular metaheuristics and describe their applicability.

The *tabu search* (TS) has been widely studied and shown to provide results that are close to optimal for many types of problems (Gendreau & Potvin 2010b). TS searches for new alternative solutions that provide the greatest improvement or least digression from the existing solution. To prevent the TS algorithm from working back toward a local optimum, a "tabu list" of previous changes is kept. The model is not allowed to undo a change on the tabu list unless doing so provides a better result than any other alternative. This approach allows the TS to focus the search by evaluating changes in new areas of the solution space. The search is terminated when certain user-defined criteria are met, such as the number of iterations, time elapsed, or consecutive iterations without improvement (Hillier & Lieberman 2015). While this method has been shown to provide near-optimal results (Gendreau & Potvin 2010b), several iterations are typically required to search for paths out of local optima rather than globally searching for the optimum (Hillier & Lieberman 2015).

Simulated annealing (SA) is a metaheuristic that is frequently used in discrete optimization. The SA procedure is modeled after the annealing of crystalline structures where they begin at a high temperature and are cooled slowly to remove defects (Nikolaev & Jacobson 2010). SA modifies an initial solution, like the tabu search, but rather than performing small, local searches, changes are made to explore the entire solution space. Improved solutions are kept, but sub-optimal ones have a certain probability of being used in the next iteration based on an initial "temperature." The temperature is high initially and results in a high probability of the algorithm accepting an inferior solution as the base for the next iteration. With each iteration, the temperature decreases, and the algorithm is less likely to accept an inferior solution. The process ends when there are a consecutive number of iterations without improvement below a user-defined minimum temperature (Hillier & Lieberman 2015).

Genetic algorithms (GAs) follow a fundamentally different method than the TS or SA approaches. They are based on the evolutionary concept that combining the "genes" from well-performing solutions can combine to produce better ones (Reeves 2010). Rather than making adjustments to a single solution, GAs make comparisons within a population. Each solution in the population has a genetic code corresponding to values of the decision variables and is assigned a level of desirability based on how well it meets the objective function. In each iteration, a new population is randomly developed by repeatedly combining the genetic information from two solutions to form new ones. The most desirable parent solutions have a higher probability of reproducing with the expectation that they will provide better "children" in the next iteration. Mutations, or random changes to the genetic code (values of the decision variables), are also applied to the population to allow for a broader search of the solution space. The process terminates in a manner similar to a TS (Hillier & Lieberman 2015).

Each of these metaheuristics has been used in the rail industry and in other maintenance planning applications. GAs have been used in a variety of maintenance planning situations (Lapa et al. 2006; Yang et al. 2008; Chen et al. 2014), and all of the methods have been used for train scheduling and routing (Burdett & Kozan 2006; Tormos et al. 2008; Corman et al. 2010; Sogin et al. 2012; Yang et al. 2012; Jamili et al. 2012; Niu & Zhou 2013; Dündar & Şahin 2013; Barrena et al. 2014; Sun et al. 2014; Xu et al. 2014; D'Ariano et al. 2014; Dewilde et al. 2014; Martínez-Salazar et al. 2014; Assadipour et al. 2015; Zhao et al. 2015; Kang et al. 2015).

When used in railway maintenance planning, metaheuristics have primarily been used for short-term planning and typically within a timetable (Higgins 1998; Lake et al. 2002; Soh et al. 2012; Zhang et al. 2013; Baldi et al. 2016). GAs have been used for longer-term maintenance planning (Grimes 1995; Zhao et al. 2009; Camci 2015) and inspection timing (Podofillini et al.

2006; Konur et al. 2015). The maintenance planning models cited here only look at the activities to be performed in their objective functions but do not consider how the maintenance is being performed. As shown in Chapter 8, window length, aggregation, and the use of detours can also affect the desirability of a maintenance plan. Having multiple independent decision variables makes it difficult to generate the genetic code required to apply a GA.

The TS is also unsuitable for application with the costing model described here because making local changes to the schedule only changes the timing on one line in the network and only over one small time period. Since the maintenance plans on each route are only linked through equipment and budget constraints, the changes to one route made by the TS are unlikely to cause the algorithm to explore new solutions on other routes in the network. These properties of the multi-route track maintenance planning problem will likely lead the TS to a local optimum for each route and make it difficult for the TS to effectively optimize the entire system.

SA overcomes the problems with both TS and GA because it can make changes to any decision variable rather than trying to combine solutions or look in a localized part of the solution space. Also, the maintenance planning model formulated in this chapter is a discrete optimization and SA is frequently used for solving these types of models (Nikolaev & Jacobson 2010).

9.4 Metaheuristic solution to maintenance planning model

To solve the multi-route track maintenance planning problem using a metaheuristic approach, an SA algorithm (Figure 9.1) is applied to improve an initial feasible solution consisting of a baseline track maintenance plan. During each iteration, the baseline maintenance plan is altered by making a random change to the current schedule. If the new maintenance plan

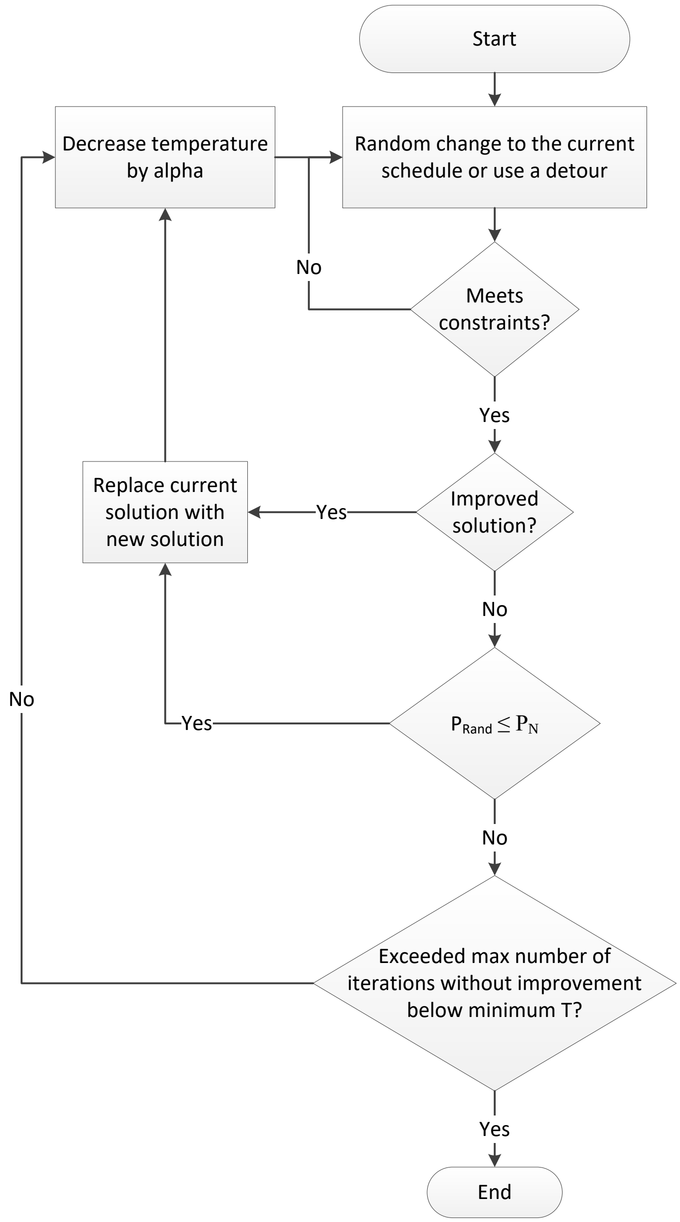

Figure 9.1: Simulated annealing flow chart

does not violate the constraints, it is evaluated according to the objective function. If the new plan has lower costs than the current one, the new plan replaces it. If the new plan has higher costs, it has an acceptance probability based on the current temperature (Equation 9.17). This is how the SA works away from local optima towards a globally optimal solution. With each iteration, the temperature is reduced (Equation 9.18) until there are a set number of iterations with no improvement below a user defined minimum temperature. As the temperature is reduced, the SA is less accepting of sub-optimal results. The values of the decision variables for the best performing solution are taken as the maintenance schedule for the multi-route track maintenance planning problem.

$$P_N = \exp\left(\frac{Z_C - Z_N}{T}\right) \qquad 9.17$$

$$T' = T\alpha \qquad 9.18$$

Where:

P_N – acceptance probability for the new plan
Z_C – cost of the current solution
Z_N – cost of the new solution
T – current temperature
T' – temperature for the next iteration
α – temperature reduction factor

The SA algorithm operates under the same assumptions as in Chapter 8. Long work windows and aggregation are only used when multiple maintenance activities are being performed in the same year. Detours can only be applied when long work windows and aggregation are used. If aggregation is used without a detour, the windows are limited to 24 hours. During each iteration, the SA algorithm may shift a maintenance activity one year earlier or later or elect to use (or not use) an available detour. These assumptions limit the potential changes available to the SA algorithm. Limiting the available changes leads to faster convergence to a solution by reducing the number of decision variables since work window length becomes a function of the number of activities being performed and detour use.

9.5 Case study

To demonstrate the multi-route track maintenance planning model and SA solution process, the model was applied to a representative case study network of four rail lines. The four routes are identical except for double track and available detours. The four combinations of double track and detour characteristics allow for a comparison of optimal maintenance plan solutions across these common operating conditions.

Each 20-mile (32-km) case study route has 30 MGT of traffic annually on Federal Railroad Administration Class 3 track (40 mph (64 km/h) maximum speed) with approximately 12 trains per day and 65-percent capacity utilization. In the absence of a manually created base maintenance plan, the number of years since capital maintenance was last performed can be used with normal maintenance cycles. For this case study, time since previous capital maintenance was assumed to ensure all activities would be scheduled for maintenance and there would be reasonable opportunities for aggregation using assumed normal maintenance cycles (Table 9.5). The values from Table 9.5 were used to develop a base maintenance plan (Table 9.6). As discussed in Chapter 7, running an optimization model over an extended planning period would likely be computationally time restrictive, so the time frame was limited to 10 years. Other parameters are the same as in other chapters and are also presented in Appendix K. Based on

Table 9.5: Capital maintenance parameters (years)

	Rail	Crossties	Ballast
Assumed time since last capital maintenance	15	3	2
Normal capital maintenance cycle	20	9	4

Table 9.6: Base maintenance plan for all routes

	x_{ijk}			b_{jk}	a_{jkw}		
Year	Rail	Crosstie	Ballast	Detour	7.5 hours	24 hours	7 days
0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0
2	0	0	1	0	1	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	1	0	0	0	1	0	0
6	0	1	1	0	0	1	0
7	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0

these assumptions, the initial schedule had a combined network cost of approximately $1.2 billion over the 10-year planning period.

To determine the most efficient SA parameters, a range of T and α were tested to find the best combination of minimized cost and solution time. Since the SA process is random, there is no guarantee that a single combination of T and α will always provide the best solution, so the combinations were tested multiple times to find average results. Exact results from individual model runs are in Appendix L.

Test results show that neither higher initial T nor α values ensure lower cost maintenance plans (Table 9.7) but always increase model runtimes (Table 9.8). These tables use heat maps to visually indicate preferred results. Since longer runtimes did not necessarily result in lower costs, the average percent improvement per minute was calculated as well (Table 9.9). The heat map in Table 9.9 is reversed from Tables 9.7 and 9.8 because higher values are more desirable.

Table 9.7: Average minimum maintenance plan costs (1x10^9 dollars)

		Initial T								
		1E+06	1E+07	1E+08	1E+09	1E+10	1E+11	1E+12	1E+13	1E+14
α	0.85	1.19	1.19	1.19	1.18	1.16	1.16	1.19	1.16	1.18
	0.90	1.19	1.19	1.17	1.15	1.17	1.18	1.16	1.18	1.18
	0.95	1.17	1.17	1.14	1.15	1.17	1.17	1.18	1.19	1.20
	0.99	1.14	1.12	1.12	1.18	1.18	1.21	1.21	1.20	1.21

Table 9.8: Average model runtimes (minutes)

		1E+06	1E+07	1E+08	1E+09	1E+10	1E+11	1E+12	1E+13	1E+14
α	0.85	3	4	4	5	5	6	6	7	7
	0.90	5	6	6	7	8	9	9	10	11
	0.95	10	11	13	14	16	18	20	21	22
	0.99	50	57	66	74	82	89	97	105	112

Table 9.9: Average percent cost reduction per minute

		Initial T								
		1E+06	1E+07	1E+08	1E+09	1E+10	1E+11	1E+12	1E+13	1E+14
α	0.85	1.02	0.99	0.85	0.90	1.17	0.99	0.53	0.94	0.56
	0.90	0.77	0.62	0.84	0.90	0.68	0.47	0.63	0.40	0.38
	0.95	0.52	0.44	0.57	0.48	0.33	0.28	0.23	0.18	0.12
	0.99	0.16	0.16	0.13	0.06	0.05	0.02	0.02	0.03	0.02

One benefit of a short solution time is that the model can be run multiple times and the solutions evaluated rather than having the model run for an extended time on a sub-optimal path. Since no single run of the SA algorithm can guarantee a lower cost than any other, running the model multiple times may be a more cost-effective way to find a least-cost maintenance plan than a single long run. Normalizing the cost improvement by the model run time is one way to help the user balance longer runtimes with the likelihood of an improved result. Based on the average percent improvement per minute of model run time, the best combination of T and α appears to be an initial T of 1 x 10^{10} and an α of 0.85. If an organization is more interested in simply finding the lowest cost maintenance plan than how long it takes to get the result, the best combination is an initial T of 1 x 10^{8} and an α of 0.99. Tests should be performed on specific applications to determine the best combination based on the user's objectives.

One of the best solutions found during the testing process provided a total cost of just over $1.1 billion. The initial T was 1 x 10^{13} with an α of 0.9 and a solution time of 11 minutes. While this solution had a cost reduction of almost 10-percent from the base plan, a second run resulted in only a six-percent cost improvement. This shows the variability between individual model runs and a potential benefit of running the model multiple times to find improved solutions. While this solution is different from the optimal initial T's and α's above, it is presented to demonstrate the solution output diversity by the model as shown by their differing optimized maintenance plans (Tables 9.10 – 9.13).

Table 9.10: Maintenance plan for the single-track route with a short detour

	x_{ijk}			b_{jk}	a_{jkw}		
Year	Rail	Crosstie	Ballast	Detour	7.5 hours	24 hours	7 days
0	0	0	0	0	0	0	0
1	0	0	1	0	1	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	1	1	1	0	0	1
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0
7	1	0	1	1	0	0	1
8	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0

Table 9.11: Maintenance plan for the single-track route with a long detour

	x_{ijk}			b_{jk}	a_{jkw}		
Year	Rail	Crosstie	Ballast	Detour	7.5 hours	24 hours	7 days
0	0	0	0	0	0	0	0
1	0	0	1	0	1	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	1	0	1	1	0	0	1
6	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0
8	0	0	1	0	1	0	0
9	0	0	0	0	0	0	0

Table 9.12: Maintenance plan for the double-track route with a short detour

	x_{ijk}			b_{jk}	a_{jkw}		
Year	Rail	Crosstie	Ballast	Detour	7.5 hours	24 hours	7 days
0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	1	0	1	1	0	0	1
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0
7	0	1	1	1	0	0	1
8	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0

Table 9.13: Maintenance plan for the double-track route with a long detour

Year	x_{ijk} Rail	Crosstie	Ballast	b_{jk} Detour	a_{jkw} 7.5 hours	24 hours	7 days
0	0	0	0	0	0	0	0
1	0	0	1	0	1	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	1	1	1	0	0	1
7	0	0	0	0	0	0	0
8	1	0	1	1	0	0	1
9	0	0	0	0	0	0	0

The optimized maintenance schedules resulted in decreased total costs for each route but did not necessarily reduce every cost category (Figure 9.2, see Appendix M for exact costs). All routes had higher direct maintenance costs, typically due to the addition of a ballast maintenance activity to the maintenance plan. The exception is the double-track route with a short detour where the cost increase was due to rail maintenance being performed earlier in the planning

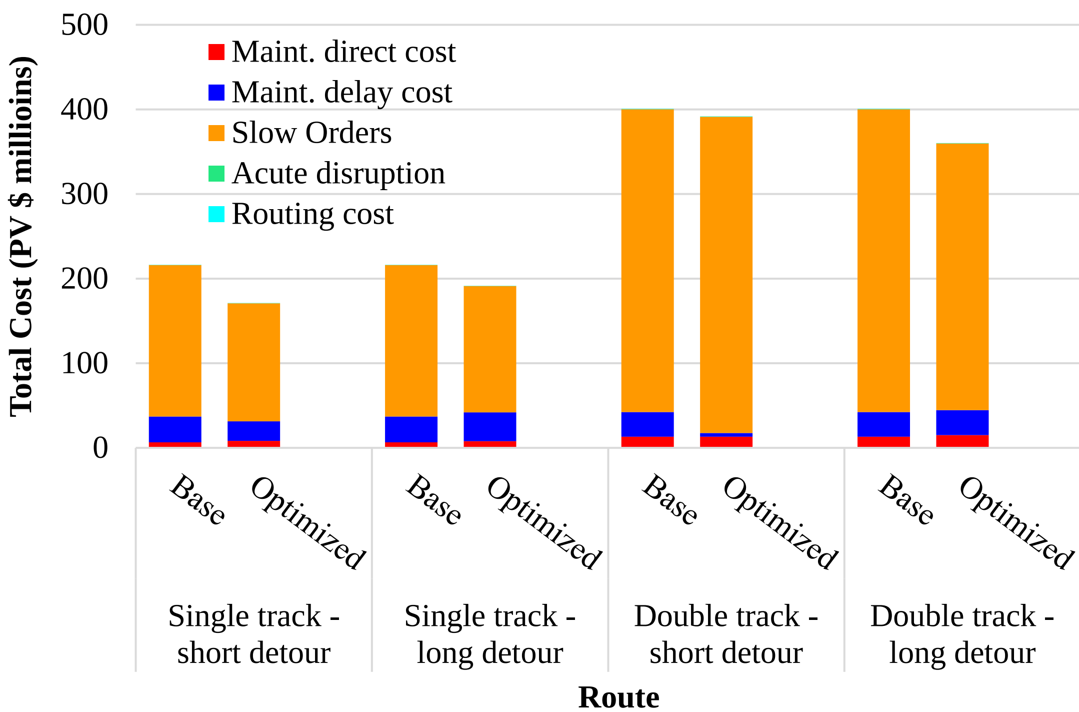

Figure 9.2: Comparison of base and optimized maintenance plan costs

period. In most cases, the increased maintenance costs are offset by substantial decreases in slow order costs. Since slow orders make up the majority of the maintenance plan costs, adding a planned maintenance activity to decrease the disruption risk decreases the total cost of the plan. Since additional maintenance was added on most of the routes, the base maintenance cycles may need to be reevaluated to see if adjustments can reduce risk in the base maintenance plan. As in previous chapters, the acute disruption costs were relatively small due to recent improvements in the track-caused derailment rate.

Comparing the results for different routes leads to additional observations:

- For both short detour routes, the maintenance-caused train delay costs decrease, with a reduction of over 85 percent on the double-track route. These reductions were achieved by aggregating nearly all maintenance events and using detours.

- The double-track short-detour route did not experience a decrease in slow order costs. This shows that additional disruption risk can be tolerated if there is enough benefit from decreased costs in other categories to reduce the overall cost.

- For the long-detour routes, there was a slight increase in delay costs due to the added maintenance events.

- Both long-detour routes utilized the detour when aggregation was used. For the single-track route, even a substantial detour was more favorable than stopping traffic and having cascading delays. Based on the findings in Chapter 4, it was hypothesized that the double-track route would not have found the long detour to be cost effective. This suggests that the extended work window greatly diminished the operational capacity of the double-track route and maintaining traffic flow on a much longer detour route was more favorable than the additional delay associated with the reduced amount of double track. This result may indicate the parametric model used to estimate train delay is poorly calibrated for the length of the case study route.

For this case, the budget and resource constraints did not to restrict the solution. This is partly because all four routes started with the same plan, so the resource limit had to be high enough to allow each activity to be performed on all routes in the same year. Even though the constraints did not limit the number of maintenance activities in a year, the model shifted maintenance so they occur on different routes in different years. This shows the potential for an optimized multi-route maintenance plan to be different than the optimal maintenance plan for each individual route. Further study examining a wider range of routes and initial maintenance plans could give more insights into how consideration of an entire network affects an optimal maintenance plan.

9.6 Conclusions and future work

This chapter describes a multi-route railroad track maintenance planning optimization model that integrates the work from the preceding chapters of this dissertation. Simulated annealing was applied to generate a solution for the model and minimize the total cost of the maintenance plan over a planning period. While SA does not guarantee a globally optimal solution, having an automated approach removes the inefficiency of manually making minor adjustments to maintenance schedules to see if there is an opportunity for improvement. The SA approach is also capable of evaluating schedule adjustments that might not normally be considered by practitioners but can further reduce costs.

The case study demonstrates how the model adjusts the schedule on the four different lines in different ways to reduce the overall total maintenance plan costs. The differences between the four plans are partially due to the different route characteristics but also the random nature of SA and consideration of equipment-routing costs. Since the random selection process may not try every adjustment that might reduce costs, the final solution may still present opportunities to further reduce costs. For example, if a route has a favorable detour that is not selected, maintenance planners can use their practical knowledge of the system to improve the plan. As another example, if similar lines have different maintenance plans in the final solution, the plans can be compared to identify potential areas for improvement. While equipment constraints did not limit the possible solutions, the inclusion of equipment-routing costs may have resulted in maintenance being performed in different years for different routes to reduce the overall costs.

After the model was completed, I realized that the formulation could be simplified to remove some of the non-linearity. This could be accomplished by replacing the decision variables, x_{ijk}, b_{jk}, and a_{jkw}, with a single variable vector that represents each combination of maintenance activities, detour use, and level of aggregation. Equations 9.7 and 9.12 could then be simplified to sum over the single decision variable. A similar approach could be taken with the disruption costs by having a variable based on the number of years since capital maintenance was last performed. This approach would require more pre-processing to enumerate every combination of maintenance and execution alternatives and calculating the associated costs. While this approach will be more intensive before running the model, removing the non-linearity associated with calculating the component costs will simplify the optimization and reduce the model run times.

Although the model presented in this chapter is functional, additional work will improve its applicability to a wider range of maintenance planning scenarios. To further integrate the practicalities of the detailed maintenance planning process, an improved equipment routing model should be developed or adapted. One way to implement a simple routing model would be to divide the planning period into months instead of years. The model could then consider when during the year maintenance is scheduled and develop a general route for the equipment. This month-based approach could also allow for constraints related to travel time between maintenance activities, the time of year maintenance can be performed on certain routes, and more exact scheduling of activities to be aggregated on the same route.

Other improvements are related to the treatment of double-track delay and detour costing. Further study is needed to determine the best way to quantify delay when maintenance is performed on double track. The model from Chapter 5 could be adapted for this purpose, but simulations would be required to calibrate the capacity adjustment factors. An additional consideration is that detouring all traffic during a maintenance event may not be necessary or desirable. An improved detour model could optimize how many and what types of trains should be detoured based on the detour and traffic characteristics. Additionally, the current detour costing formulation only considers rerouting onto a competing railroad; an available parallel route owned by the original railroad would likely be a lower-cost option. Determining these reroute costs requires a method to estimate delay and additional track degradation on the detour route, along with the additional operating costs for the detoured trains. This method could follow the same detour costing formulation used in this model by converting the costs on the detour line to a millage rate. While these topics are beyond the scope of this dissertation, they can improve both this model and the general understanding of maintenance costing.

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CHAPTER 10.

CONCLUSIONS AND FUTURE WORK

10.1 Conclusions

Track maintenance decision support tools have the potential to help railroads perform maintenance more efficiently. This would permit more effective use of the same budget or reduce maintenance expenditures. For these benefits to be realized, it is necessary to quantify all the costs associated with a maintenance plan, including indirect costs related to train delay and disruptions. Any analysis that fails to include these secondary costs is neglecting large portions of expenditures affected by maintenance timing. This is especially true when maintenance schedules are adjusted or initially determined because deferring maintenance increases disruption risk. This relates to the direct cash flow (DCF) trap discussed in Chapter 1 and the integrated maintenance planning framework described in Chapter 2.

Integrating the track evaluation step of maintenance planning is required to account for disruption risk. Without having a way to determine the track condition or failure probabilities, it would be difficult, if not impossible, to quantify how adjustments to the maintenance plan affect disruption risk. Several chapters show that disruption risk is a large portion of track ownership costs, so not including it may result in maintenance being deferred and a higher overall cost of ownership. The same could be true with equipment routing costs. Optimizing the plan based only on maintenance and disruption costs could result in work being performed in disparate regions of the network. While this could be the ideal for those individual routes, it might be infeasible to transport equipment and crews between the maintenance sites or result in inefficient equipment routing. Since most of this dissertation is focused on maintenance of individual lines, equipment routing costs are not generally considered. If multiple lines or sections of track are considered, as discussed in Chapter 9, equipment routing also becomes important to ensure that the all the scheduled maintenance can be performed and are being assigned efficiently.

A cost related to both maintenance and disruptions is train delay. As shown throughout this dissertation, particularly in Chapters 6 and 7, delay can contribute a substantial portion of both maintenance and disruption costs. While these costs can be calculated in a variety of ways, consistency across all situations is necessary for reliable comparisons. The delay costing methodology in Chapter 3 and delay estimation model in Chapter 5 provide novel ways to estimate delay costs and ensure that the complete cost of delay is included.

Finally, incorporating these into a risk-based costing model in Chapter 7 allows for a comprehensive view of a maintenance plan. Applying optimization tools to this model provides a way to improve the performance of a network while considering practical constraints such as the budget and equipment availability. Although the optimization model presented in Chapter 9 does not guarantee a globally optimal solution, it can find lower cost alternatives. Due to the random nature of simulated annealing, maintenance personnel may be able to use their experience and judgment to make simple changes and find an even lower cost maintenance plan. In the end, that is the point of decision support tools. They are not meant to replace personal experience, but rather to augment and enhance it by providing novel insights and objective analysis.

10.2 Future work

Much of the potential future work for this dissertation is related to the individual research components and is discussed in their respective chapters, but there are a few overarching concepts. One key area for improvement that is mentioned repeatedly throughout this dissertation is the need for data either for validation or developing new models. Many of the models and cost data used throughout this dissertation are dated and may no longer be representative of current operations. Specific areas for which new data would be beneficial are development of new disruption models and validation of the direct maintenance costs models. Improved understanding of how disruption risk changes over time and based on operating conditions would help ensure that the costs to change maintenance schedules are accurately quantified. While the analyses in this dissertation assume that direct maintenance costs do not change through time and are relatively small, their timing directly affects the disruption risk. If direct maintenance costs in the model are higher than in practice, the model will likely be more tolerant of disruptions to balance the costs. Additionally, the relative costs for different work window lengths could have a large effect on the desirability of adjusting maintenance schedules to take advantage of aggregation. In both cases, the relative values between direct and disruption costs will drive the maintenance plan composition.

A related topic that could use the concepts developed in this dissertation is determining optimal maintenance cycles. The assumed maintenance cycles used here are largely based on analysis or industry practice, but may not be ideal. Using a risk-based approach, the most cost-effective maintenance cycles could be determined for specific components to balance the independent direct maintenance costs with the component-specific disruption risk. These improved independent cycles would provide a better starting point for the metaheuristic and result in a better final plan. If integrated track degradation models were found or developed, simplified risk-based costing could be done to optimize each of the component maintenance cycles. This initial plan could then be analyzed using the metaheuristic to determine how aggregation on long work windows or detours could further reduce costs.

In addition to improving the component parts of this research, further exploration of the integrated maintenance-planning framework would allow for a more comprehensive view of the maintenance plan costs. This dissertation focused on the evaluation of a maintenance plan that ended up requiring degradation models to determine disruption risk, but the maintenance routing step is not as integrated. The optimization model in Chapter 9 included a simplified routing cost model. Development or adoption of a more robust method to assess equipment routing cost would provide better overall maintenance plan costs and allow for more effective solutions. Even though degradation models were adapted and developed for use in this research, they can be further improved. This work could consist of improved track-component-specific models, or more ideally, one that comprehensively evaluates track condition. Continuously updating the models for each step of the maintenance planning process and their integration will allow an ever-improving understanding of the costs associated with a maintenance plan and how to reduce them.

APPENDIX A.

TRAIN DELAY COST INPUT PARAMETERS

Crew costs were computed using the service hours and total compensation from the Surface Transportation Board (STB) wage statistics for Group 600: Transportation (Train & Engine) (Surface Transportation Board 2016).

$$Crew\ wage = \frac{Total\ compensation}{service\ hours}$$

$$= \frac{6{,}066{,}189{,}000}{176{,}453{,}620}$$

$$= 34.38$$

Locomotive fuel costs were calculated using the notch occupancy values (U. S. Environmental Protection Agency 1998) and fuel consumption rates (Frey & Graver 2012) (Table A.1). The weighted average was taken as the average hourly fuel use.

Table A.1: Fuel use based on throttle notch position

Throttle Position	Notch occupancy (%)[1]	Fuel use (g/sec)[2]
Idle	38.0	5.9
Dynamic Brake	12.5	8.7
1	6.5	11.5
2	6.5	21.6
3	5.2	44.9
4	4.4	68.3
5	3.8	89.2
6	3.9	126
7	3.0	154
8	16.2	176
Weighted average		52.26

1. (U. S. Environmental Protection Agency 1998)
2. (Frey & Graver 2012)

Using the conversion of 3,200 grams of diesel per gallon (Frey & Graver 2012), the average fuel consumption rate is

$$fuel\ consumption\ per\ hour = \frac{52.29}{3200} \times 3600$$

$$= 58.79\ gal/hr$$

Locomotive operating expense was calculated by dividing the total locomotive expense including depreciation (Line 150 in the AAR Analysis of Class I Railroads) by the average number of locomotives per train (Line 725) and the total number of train hours (Line 712) (Association of American Railroads 2015). For 2014, this would be

$$Op.\ expense\ per\ loco - hour = \frac{Loco\ cost}{\frac{locos}{train} \times (train - hour)}$$

$$= \frac{4{,}865{,}608{,}000}{2.7 \times 29{,}359{,}822}$$

$$= 61.38$$

Manifest revenue was calculated by taking the weighted average from the table below for all categories except “All Other” (Association of American Railroads 2015) (Table A.2).

Table A.2: Carloads and revenue by category (Association of American Railroads 2015)

	Carloads originated	Gross revenue (1,000s)
533. Grain (Including Soybeans)	1,467,498	5,607,375
534. Other Farm Products	136,742	526,075
535. Metallic Ores	843,565	772,027
536. Coal	6,110,053	14,343,557
537. Crushed Stone, Gravel and Sand	1,310,531	3,451,898
538. Non-Metallic Minerals	272,290	562,888
539. Grain Mill Products	610,721	2,183,232
540. Food and Kindred Products	1,003,704	3,654,405
541. Primary Forest Products	108,640	175,643
542. Lumber and Wood Products	243,881	1,766,827
543. Pulp, Paper and Allied Products	714,199	2,342,380
544. Chemicals and Allied Products	2,233,456	10,440,277
545. Petroleum Products	407,510	2,105,450
546. Stone, Clay and Glass Products	479,087	1,943,354
547. Coke	200,598	433,601
548. Metals and Products	690,289	2,927,260
549. Motor Vehicles and Equipment	1,183,002	5,530,037
550. Waste and Scrap Material	594,480	1,312,277
551. Forwarder and Shipper Association	176,100	267,967
Sum	18,786,346	60,346,530

$$Manifest\ revenue\ per\ car = \frac{60{,}346{,}530 \times 1000}{18{,}786{,}346} = 3{,}212$$

The empty return ratios were calculated by dividing the empty car-miles by the loaded car miles for all but category “Flat TOFC/COFC,” that are primarily used for intermodal service (Association of American Railroads 2015) (Table A.3).

Table A.3: Loaded and empty car-miles by category (Association of American Railroads 2015)

Car types	Loaded car-miles	Empty car-miles
659. Box - Plain 40'	0	3
660. Box - Plain 50'	126,335	87,324
661. Box - Equipped	921,576	719,118
662. Gondola - Plain	3,228,887	3,174,972
663. Gondola - Equipped	456,785	406,773
664. Covered Hopper	4,059,152	3,972,749
665. Open Hopper - General Service	533,346	539,306
666. Open Hopper - Special Service	1,812,789	1,791,540
667. Refrigerator - Mechanical	169,904	129,643
668. Refrigerator - Non-Mechanical	67,495	58,575
670. Flat Multi-level	1,548,106	705,722
671. Flat General Service	1,862	2,507
672. Flat All Other	584,752	537,476
673. Tanks	2,976,959	3,052,511
674. All Other Types	332,290	80,393
Total	16,820,238	15,258,612

$$Empty\ return\ ratio = \frac{16{,}820{,}238 + 15{,}258{,}612}{16{,}820{,}238} = 1.91$$

The lost revenue from railcar delay can then be calculated using Equation 3.5 as

$$C'_G = \frac{2 \times 3212 \times 0.75}{(26.88 \times 24) \times 1.91} = 3.91$$

To calculate Intermodal based on STCC 7 Stratification report the following data was used (Surface Transportation Board 2015) (Table A.4).

Table A.4: Number, weight, and revenue by intermodal car type

Car type	Sum of cars	Sum of tons (1000s)	Sum of revenue (1000s)
Intermodal	448	5.944	969.568
Lightweight Intermodal	142240	1158.92	84430.043
Stack Car	12792880	163280.76	12201383.29
Grand Total	12935568	164445.624	12286782.9

$$Intermodal\ revenue\ per\ car = \frac{12{,}286{,}782{,}900}{12{,}935{,}568} = 950$$

$$Intermodal\ Empty\ return\ ratio = \frac{4{,}453{,}708 + 355{,}547}{4{,}453{,}708} = 1.08$$

The lost revenue from railcar delay can then be calculated using Equation 3.5 as

$$C'_G = \frac{2 \times 950 \times 0.75}{(6.15 \times 24) \times 1.08} = 8.94$$

To determine intermodal lading value the following data was used (Center for Transportation Analysis 2017) (Table A.5).

Table A.5: Weight and value of assumed intermodal goods by category

Product category	Total KTons in 2015	Total ton-mile in 2015	Total M$ in 2015	Total current M$ in 2015
Furniture	80794	35136	386601	400526
Misc. manufactured products	105637	46862	790805	809615
Mixed freight	386063	99019	1458339	1486426
Sum	572494	181016	2635745	2696567

$$Intermodal\ lading\ value = \frac{2696567 \times 1000000}{572494 \times 1000} = 4710$$

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APPENDIX B.

USING THE WEIBULL DISTRIBUTION FOR TIMBER CROSSTIE MAINTENANCE PLANNING

B.1 Introduction

Over 16.5 million railroad crossties were laid in 2012, of these over 94% were timber (Association of American Railroads 2012). Due to the large number of crossties that need to be maintained, it is important to understand what the failure distribution is in order to plan when crossties will need to be replaced. While most railroad track components degrade at a rate relative to the number and magnitude of the load cycles they must resist, timber crossties are also impacted by the environment. For this reason, the life of crossties is typically reported in years rather than million gross tons (MGT), which is the standard age metric for railroad components (MacLean 1957; Zarembski & Gauntt 1997; Lake et al. 2002).

To better understand how to plan for the replacement of timber crossties, one common model used to predict the failure of timber crossties will be analyzed and applied to two maintenance cases: large-scale renewals and slow orders.

Some recent research has gone into determining the average life of crossties for given environmental conditions, annual tonnage, and curvature, each of which will result in different crosstie lifespans (Zeta-Tech Associates Inc. 2006). However, since it is generally accepted that not all crossties will fail at the same time simply knowing the average time when crossties will fail is not enough. The number of crossties that are expected to fail in a given year is also required so that when the critical number of crossties are expected to fail, a crosstie replacement can be planned.

B.2 Determining timber crosstie failure probabilities

The generally accepted method for modeling crosstie failures is to apply the Forest Service Products Curve (FSPC), which was developed to predict the failure distribution of timber crossties. While the FSPC is dated, multiple updates have affirmed the accuracy of the model (MacLean 1957; Wells 1982). Personal discussion with railroad personnel indicates that this model is still in use. However, this model in its original form is a chart that can be read off rather than an equation than can be used to calculate the failure rates directly (Figure B.1) (MacLean 1957; Wells 1982). This method uses the percentage of average life as the random variable, which allows for the distribution to be less dependent on operating conditions.

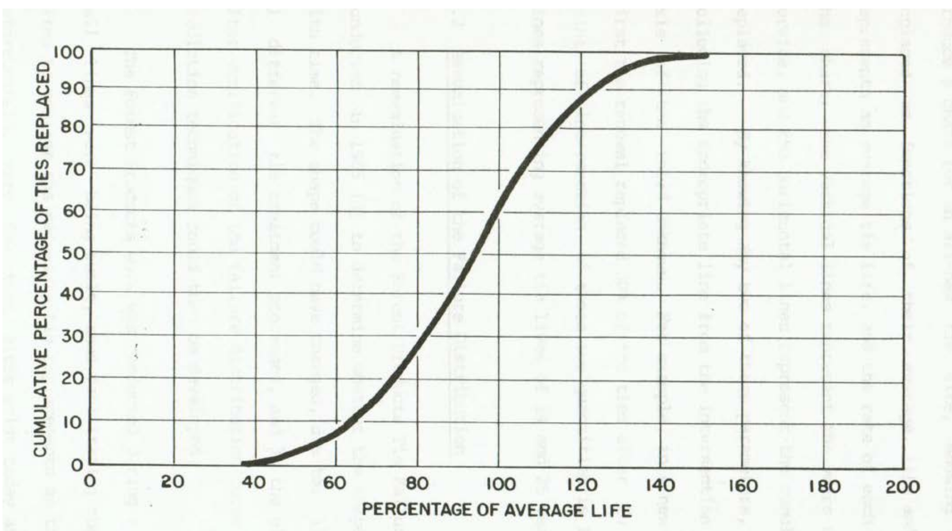

Figure B.1: Forest service products curve (Wells 1982)

A common distribution used as a fragility curve for similar components is the Weibull distribution. The two parameters of the Weibull distribution are α, the shape factor, and β, the scale factor. (Arthur D. Little Inc. 1992; Lake et al. 2002; Kroese et al. 2011; Lovett et al. 2013). The PDF and CDF for the Weibull distribution are given in Equations B.1 and B.2 (Kroese et al. 2011).

$$f_T(t) = \begin{cases} \frac{\alpha}{\beta}\left(\frac{t}{\beta}\right)^{\alpha-1} \exp\left(-\left(\frac{t}{\beta}\right)^{\alpha}\right), & t, \alpha, \beta > 0 \\ 0, & else \end{cases} \quad \text{B.1}$$

$$F_T(t) = \begin{cases} 1 - \exp\left[-\left(\frac{t}{\beta}\right)^{\alpha}\right], & t, \alpha, \beta > 0 \\ 0, & else \end{cases} \quad \text{B.2}$$

Where:

- t – proportion of average life= $\frac{y}{A}$
- y – number of years since the crosstie was installed
- A – average crosstie life
- α,β – Weibull parameters

If the mean and standard deviation data had been provided, they could have been used to calculate α and β, but since they were not, the curve in Figure B.1 was fitted to a Weibull distribution using the least squares regression method (Table B.1, Figure B.2). This method consists of minimizing the sum of the square of the difference between the reported values and the estimated values given by the equation (Bates & Watts 1988; Weisstein 2014a). The square of the difference is used because it allows for the difference, or residual, to always be positive, which avoids discontinuities (Weisstein 2014b). Figure B.2 shows that the Weibull approximation closely matches the provided curve. The minimization was done in Excel using the built-in solver. The values used for the regression are provided in the sub-appendix.

Table B.1: Weibull parameters from the least squares regression

Weibull Parameter	Value
α	4.56
β	1.02

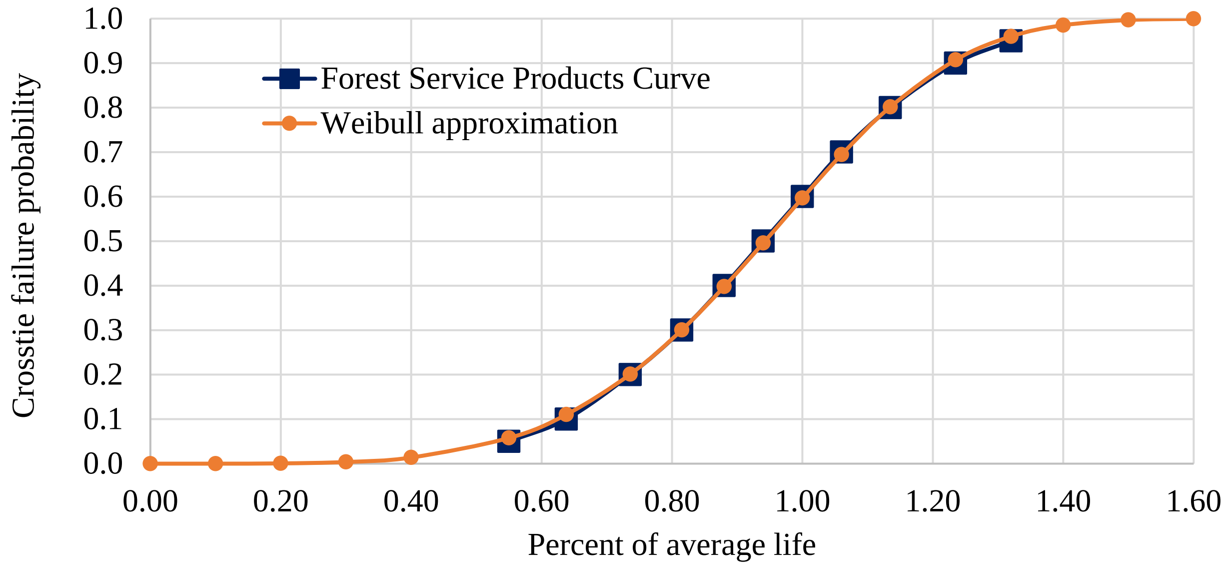

Figure B.2: FSPC and Weibull approximation

B.3 Approximating time to large-scale crosstie replacement

A common way of determining when a crosstie replacement needs to be planned is to estimate when a certain number of crossties have failed and then replacing all of the failed crossties. The typical way of doing this is to apply the FSPC to the number of crossties in a mile of track (i.e. multiply the total number of crossties in a mile by the expected percentage of failed crossties at a given age), and a crosstie renewal is planned for the year when that product is expected to be over a certain value (Elkaim et al. 1983; Davis 1988). However, this method does not take into account that each crosstie is behaving independently, a more comprehensive way would be to treat the percentage of crossties failed from the FSPC as the probability that a crosstie has failed, which can be used in a binomial distribution to determine the probability that the desired number of crossties have failed in a given year (Equation B.3). This methodology assumes that the crosstie failures are statistically independent, and while this is not entirely true, no data on this relationship was found in the literature.

$$
\begin{aligned}
P(Q > q) &= 1 - P(Q \leq q) \\
&= 1 - \sum_{i=0}^{q} \binom{n}{i} p^i \times (1-p)^{n-i}, \qquad n \geq q
\end{aligned}
\tag{B.3}
$$

Where:

- Q – number of failed crossties per mile
- n – number of crossties per mile
- p – probability that a crosstie has failed by a given proportion of the average crosstie life according to Equation B.2

Other variables as previously defined

The value of Q is typically between 600-1000 crossties per mile (Davis 1987; Acharya 1994). However, research has shown that the crosstie replacement cost decreases until approximately 800 crossties are replaced per mile at which point the cost per crosstie replaced levels out. Furthermore, the equipment begins to have problems when more than 1,000 crossties are replaced per mile because the various machinery is too close together (Elkaim et al. 1983). Therefore, it was determined that 800 crossties per mile would be a reasonable maintenance threshold. A typical crosstie spacing is 20”, which results in 3168 crossties per mile. Assuming 50 MGT annual tonnage, a range of track curvature, and a moderate climate, the average crosstie life is 31.5 years (Zeta-Tech Associates Inc. 2006). Using this data and the Weibull distribution, it is possible to create a model that will provide the probability that a crosstie replacement will need to be planned (Equation B.4).

$$
P(Q > 800) = 1 - \sum_{i=0}^{800} \binom{3168}{i} p^i \times (1-p)^{3168-i}
\tag{B.4}
$$

However, this formulation will be difficult to compute and preliminary attempts with Excel and MATLAB failed to calculate the combinations necessary for the summation. In this case, it may be more applicable to use the expected value for Q, which, for binomial distribution in Equation B.4, is the same as multiplying the number of crossties per mile by the failure probability (Equation B.5).

$$E[Q] = np = n\left(1 - \exp\left[-\left(\frac{t}{1.02}\right)^{4.56}\right]\right) \tag{B.5}$$

From Equation B.5, the time of the first replacement cycle can be calculated as shown below.

$$E[Q] = \ n\left(1 - \exp\left[-\left(\frac{t}{1.02}\right)^{4.56}\right]\right)$$

$$t = 1.02 \ \times \ \left(-\ln\left(1 - \frac{E[Q]}{n}\right)\right)^{\frac{1}{4.56}}$$

$$= 1.02 \ \times \ \left(-\ln\left(1 - \frac{800}{3168}\right)\right)^{\frac{1}{4.56}}$$

$$= 0.7781$$

$$y = A \ \times \ t$$

$$= 31.5 \ \times \ 0.7781$$

$$= 24.5$$

This indicates that the crosstie replacement would need to be performed in the 25th year after the crossties were initially installed. As crossties of various ages are left in the track after each renewal, Equation B.5 can be applied to each age group of crossties. However, there will be some variability in how the crossties actually fail, so the track inspectors can advise the maintenance planners if a crosstie renewal will need to take place sooner or later than expected.

B.4 Determining the probability of slow orders

Another area of concern for the number of failed crossties is the Track Safety Standards (TSS) which are regulated by the Federal Railroad Administration. The TSS specify the required condition of the track for specific operating speeds, which are divided into track classes. Higher track classes allow for higher permissible speeds. One of the parameters governed by the TSS is the number of crossties required for every 39 feet of track. This number varies based on the track class and the amount of curvature (Table B.2) (Federal Railroad Administration 2014).

Table B.2: Minimum number of crossties per 39 feet (Federal Railroad Administration 2014)

FRA Track Class	Tangent track and curves $\leq$ 2 degrees	Turnouts and curved track over 2 degrees
Class 1	5	6
Class 2	8	9
Class 3	8	10
Class 4 and 5	12	14

If the specifications in the TSS are violated for a given track class then the track speed must be reduced to the next class which the track is in compliance. This is known as a slow order. To understand the risks of a slow order being imposed, the probability of the number of allowable bad crossties being exceeded can be modeled with a binomial distribution similar to equation B.3. Due to the shorter distance being modeled, it can be computed directly (Equation B.6).

$$P(S_{39}) = P(G < g)$$
$$= P(B \geq b)$$
$$= P(B \geq m - g)$$
$$= 1 - P(B \leq m - g)$$
$$= \begin{cases} 1 - \sum_{i=0}^{m-g} \binom{m}{i} p^i \times (1-p)^{m-i}, & m \geq g \\ 0, & else \end{cases} \qquad \text{B.6}$$

Where:

- S_{39} – event where a 39-foot section of track must be slow ordered
- G – number of good crossties per 39 feet
- B – number of failed crossties per 39 feet
- m – number of crossties per 39 feet

Assuming the track is Class 4 with curves no more than 2 degrees and 20-inch crosstie spacing, similar to the case referenced above, each 39-foot track segments requires at least 12 good crossties. This would change Equation B.6 to equation B.7 below.

$$P(S_{39}) = 1 - \sum_{i=0}^{11} \binom{23}{i} p^i \times (1-p)^{23-i} \qquad \text{B.7}$$

This curve can be used with the cost of a slow older to understand the risks of delaying crosstie replacement because the longer maintenance is delayed the higher the probability of not having enough good crossties.

This probability can also be taken as the mean rate of occurrence for a slow order over 39 feet and can be applied to a Poisson distribution for a longer distance. This is shown in Equation B.8 for 1 mile, although this could be applied over a longer distance as well. This would be important for maintenance planning purposes because large scale crosstie replacements are done on several miles of track at a time. The plot of how the slow orders change over time is shown in Figure B.3. The values used in producing the graph are provided in the sub-appendix.

$$
\begin{aligned}
P(S_m) &= P(R > 1) \\
&= 1 - P(R = 0) \\
&= 1 - \frac{(\lambda d)^0}{0!}\exp(-\lambda d) \\
&= \begin{cases} 1 - \exp(-\lambda d)\,, & \lambda, d > 0 \\ 0, & else \end{cases}
\end{aligned}
\qquad \text{B.8}
$$

Where:

S_m – event where at least one 39-foot section in a mile has a slow order
R – number of slow ordered sections
λ – mean rate of slow order occurrence over 39 feet, $P(S_{39})$
d – number of 39-foot segments in a mile, 135.4

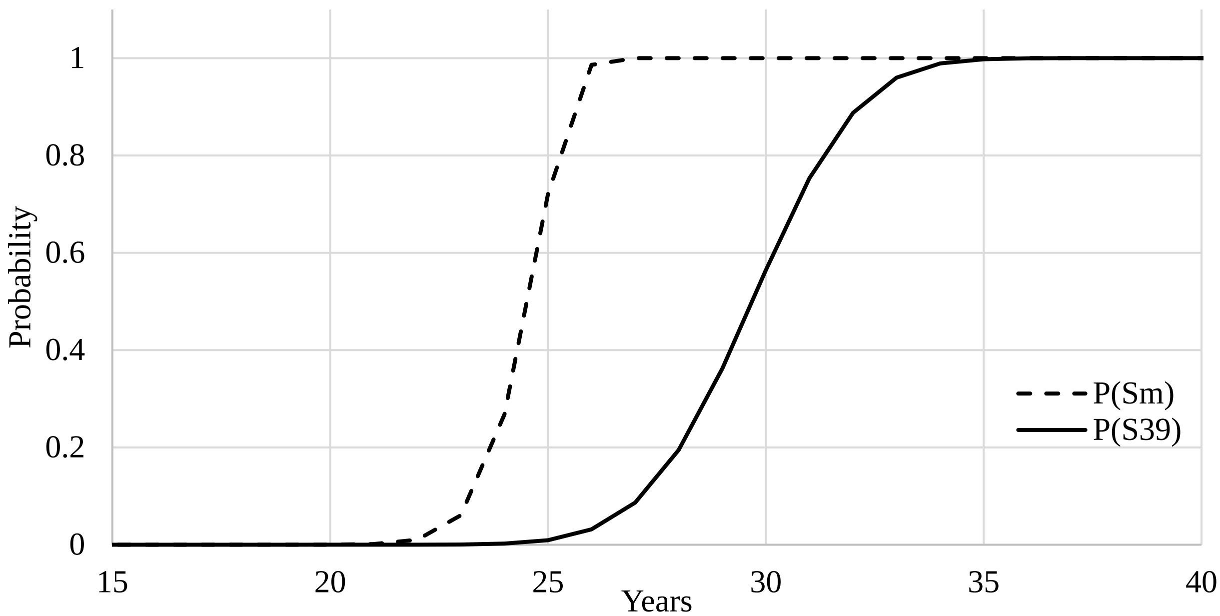

Figure B.3: Probability of a single 39-foot section and a mile of track requiring a slow order

B.5 Adjustments for track with multiple ages of track

While these formulations are beneficial for planning crosstie renewals for new track, there is not much new track being installed. Most track has been in for many years, so the crossties will have a variety of ages. This results in the binomial distribution no longer being applicable for determining the probability of a slow order. In this case, the segment of track would still be modeled as a series of Bernoulli trials, but each group of crossties of a particular age would need to be treated independently. This also results in the failure probability calculation changing. This would change Equation B.7 into Equation B.9 and Equation B.2 into Equation B.10, while Equation B.8 would remain the same.

$$P(S_{39}) = \begin{cases} 1 - \sum_{\sum i_j = 0}^{11} \prod_{j=1}^{k} \binom{n_j}{i_j} p_j^{i_j} \times \left(1 - p_j\right)^{n_j - i_j}, & n_i \geq j_i \forall i \\ 0, & else \end{cases} \qquad \text{B.9}$$

$$p_j = 1 - \exp\left[-\left(\frac{y + (j-1)c}{\beta A}\right)^{\alpha}\right], \qquad t > 0 \qquad \text{B.10}$$

Where:

- i_j – number of failed crossties in crosstie age group j
- k – number of crosstie age groups
- n_j – number of crossties in crosstie age group i
- p_j – failure probability of a crosstie in crosstie age group j
- y – years since the last crosstie renewal
- c – years between crosstie renewals

This formulation requires some assumptions as to what a typical crosstie renewal would be and calculating the number of crossties that are expected to still be in track in a given year. Assuming 850 crossties per mile, approximately 6 crossties per 39 feet, are replaced every nine years we can determine the number of crossties that are still in track at the time of a renewal. This is done by adapting a process from Elkaim et al. (1983) (Table B.3). Figure B.3 can also be updated, but only the first nine years need to be plotted since at that point all failed crossties are expected to have been replaced (Figure B.4). This new formulation can be used to weigh different crosstie renewal cycles by determining the slow order risks associated with longer or shorter periods between crosstie renewals. The values and code used for developing this plot are provided in the sub-appendix.

Table B.3: Expected number of crossties remaining per 39-foot segment from previous crosstie renewals

Renewal number (j)	Year of renewal	Percent of crossties left in track in 2013	Expected number of good crossties in 39 feet
1	2013	100%	6
2	2004	100%	6
3	1995	93%	6
4	1986	64%	4
5	1977	19%	1
6	1968	1%	0
7	1959	0%	0

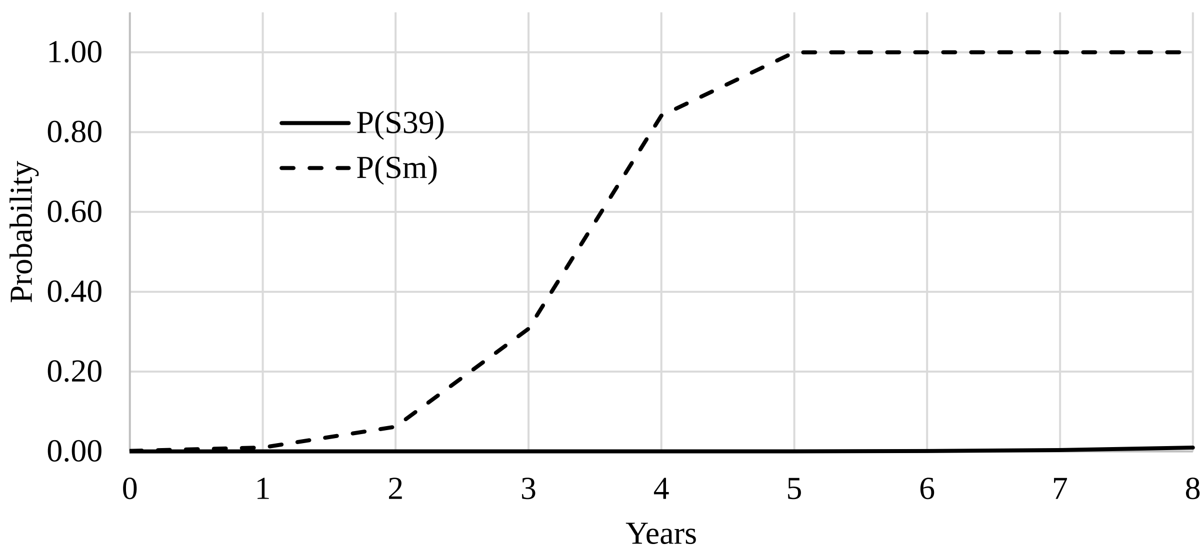

Figure B.4: Probability of a single 39-foot section and a mile of track requiring a slow order with multiple crosstie ages

B.6 Updating the FSPC

As mentioned above, the data used in developing the FSPC is quite old and may not be applicable to the current operating conditions in all areas. While the original data is not available to develop the curve directly, it is possible to use new failure data and Bayesian updating to adjust the Weibull approximation to reflect data that has been collected in a particular area.

Assume a track inspector sampled the condition and ages of crossties in a particular area (Table B.4).

Table B.4: Observed ages and conditions of crossties

Tie age (years)	Tie condition
1	Failed
1	Not failed
1	Not failed
10	Failed
10	Failed
10	Not failed
19	Not failed
19	Failed
28	Failed
37	Not failed

The standard form of the Bayesian update is shown in Equation B.11.

$$f''(\boldsymbol{\theta}) = uL(\boldsymbol{\theta})f'(\boldsymbol{\theta}') \qquad \text{B.11}$$

Where:

u – scaling constant
$\boldsymbol{\theta}$ – variable parameters to be updated
f '($\boldsymbol{\theta}$) – prior distribution
L($\boldsymbol{\theta}$) – likelihood function
f "($\boldsymbol{\theta}$) – posterior distribution

The likelihood is proportional to the probability of an observation occurring, which would be the product of the probability of each individual observation. This would be Equation B.2 evaluated at the given year since the provided data is censored. The prior distribution is equal to Equation B.1. This would change Equation B.11 into Equation B.12. The value for u was found numerically using Excel and VBA code that is contained in the sub-appendix. A diffuse prior is assumed for α and β, and the prior values are those given in Table B.1.

$$f''(t,\alpha,\beta) = uL(\alpha,\beta)f'(t,\alpha',\beta') \qquad \text{B.12}$$

Where:

$$u = \left(\int_0^\infty \int_0^\infty \int_0^\infty \left(1-\exp\left(-\left(\frac{1}{\beta}\right)^{\alpha}\right)\right) \times \left(1-\exp\left(-\left(\frac{10}{\beta}\right)^{\alpha}\right)\right)^2 \times \left(1-\exp\left(-\left(\frac{19}{\beta}\right)^{\alpha}\right)\right) \right.$$

$$\times \left(1-\exp\left(-\left(\frac{28}{\beta}\right)^{\alpha}\right)\right)$$

$$\times \exp\left(-\left(2 \times \left(\frac{1}{\beta}\right)^{\alpha} + \left(\frac{10}{\beta}\right)^{\alpha} + \left(\frac{19}{\beta}\right)^{\alpha} + \left(\frac{37}{\beta}\right)^{\alpha} + \left(\frac{t}{\beta'}\right)^{\alpha'}\right)\right)$$

$$\left. \times \frac{\alpha'}{\beta'}\left(\frac{t}{\beta'}\right)^{\alpha'-1} d\alpha\, d\beta\, dt\right)^{-1} = 24.17$$

$$L(\alpha,\beta) = \left(1-\exp\left(-\left(\frac{1}{\beta}\right)^{\alpha}\right)\right) \times \left(1-\exp\left(-\left(\frac{10}{\beta}\right)^{\alpha}\right)\right)^2 \times \left(1-\exp\left(-\left(\frac{19}{\beta}\right)^{\alpha}\right)\right)$$

$$\times \left(1-\exp\left(-\left(\frac{28}{\beta}\right)^{\alpha}\right)\right) \times \exp\left(-\left(2 \times \left(\frac{1}{\beta}\right)^{\alpha} + \left(\frac{10}{\beta}\right)^{\alpha} + \left(\frac{19}{\beta}\right)^{\alpha} + \left(\frac{37}{\beta}\right)^{\alpha}\right)\right)$$

$$f'(t,\alpha,\beta) = \frac{\alpha'}{\beta'}\left(\frac{t}{\beta'}\right)^{\alpha'-1} \exp\left(-\left(\frac{t}{\beta'}\right)^{\alpha'}\right)$$

Point estimates for α and β, $\hat{\alpha}$ and $\hat{\beta}$ respectively, can be found using Equations B.13 and B.14. These were also found through numerical integration and the code is provided in the sub-appendix. Due to computation limitations, the increment for α and β was limited to 1, but the increment for t was set to 0.01. Additionally, increasing the maximum integration value for α and β from 1,000 to 10,000 and t from 100 to 1000 did not change the values of u, $\hat{\alpha}$, or $\hat{\beta}$.

$$\hat{\alpha}'' = \int_0^\infty \alpha \int_0^\infty \int_0^\infty 24.17 \times L(\alpha,\beta) \times f'(t,\alpha',\beta') dt\, d\beta\, d\alpha = 0.5046 \qquad \text{B.13}$$

$$\hat{\beta}'' = \int_0^\infty \beta \int_0^\infty \int_0^\infty 24.17 \times L(\alpha,\beta) \times f'(t,\alpha',\beta') dt\, d\alpha\, d\beta = 44.39 \qquad \text{B.14}$$

It should be noted that updating the FSPC in this manner would result in crosstie performance no longer being statistically independent because the updated distribution will be based on condition of other crossties that had previously failed.

B.7 Developing a new FSPC

Rather than trying to update the existing FSPC, it may be beneficial to create a new curve based on specific operating conditions. This would result in a simpler formulation than the Bayesian update as the equation would be the Weibull distribution without having the likelihood function. This could be done using maximum likelihood estimates (MLEs). The general theory of MLE is that the most likely value of an unknown parameter is the value which results in the observed events having the highest probability. The general form of the MLE is shown in Equation B.15 and the MLE form for the Weibull is giving in Equation B.16. The maximum value of the unknown values **θ** can be found by setting the derivative of the likelihood function to 0 with respect to each of the Weibull parameters, which are shown in Equations B.17 and B.18. The derivation of Equations B.17 and B.18 is shown in the sub-appendix.

$$L(\theta) \propto \prod_{i=1}^{n} f(x|\boldsymbol{\theta}) \qquad \text{B.15}$$

$$L(\alpha,\beta) \propto \prod_{i=1}^{n} \frac{\alpha}{\beta}\left(\frac{t}{\beta}\right)^{\alpha-1} \exp\left(-\left(\frac{t}{\beta}\right)^{\alpha}\right) \qquad \text{B.16}$$

$$\frac{\partial \ln L}{\partial \beta} = \frac{-n \times \alpha}{\beta} + \alpha \times \beta^{-(\alpha+1)} \sum_{i=1}^{n} {t_i}^{\alpha} \qquad \text{B.17}$$

$$\frac{\partial \ln L}{\partial \alpha} = \frac{n}{\alpha} + \sum_{i=1}^{n} \ln t_i - n \times \ln \beta - \beta^{-\alpha} \sum_{i=1}^{n} t_i^{\alpha} \times \ln x + \beta^{-\alpha} \ln \beta \sum_{i=1}^{n} t_i^{\alpha} \qquad \text{B.18}$$

By setting Equation B.17 equal to zero, the point estimate for β, $\hat{\beta}$, can be found and is shown in Equation B.19.

$$\hat{\beta} = \left(\frac{1}{n}\sum_{i=1}^{n} {t_i}^{\alpha}\right)^{\frac{1}{\alpha}} \qquad \text{B.19}$$

However, the point estimate for α, $\hat{\alpha}$, is more complicated to compute. Therefore, a simplified equation taken from Balakrishnan & Kateri (2008) can be used to find $\hat{\alpha}$. This is shown in Equation B.20 (Balakrishnan & Kateri 2008).

$$\frac{1}{\alpha} = \frac{\sum_{i=1}^{n} t_i^{\alpha} \times \ln(t_i)}{\sum_{i=1}^{n} t_i^{\alpha}} - \frac{1}{n}\sum_{i=1}^{n} \ln(t_i) \qquad \text{B.20}$$

Balakrishnan & Kateri (2008) show that the right side of the equation is non-decreasing, and the left-hand side is a decreasing function. This means that there is a unique solution to the system of equations. Example data can be used to show how this could be applied (Table B.5).

Table B.5: Observed crosstie failure data

Tie	Age at failure	Percent of average life
1	10	32%
2	15	48%
3	19	60%
4	21	67%
5	26	83%
6	27	86%
7	28	89%
8	30	95%
9	32	102%
10	36	114%

The built-in solver in Excel was used to find $\hat{\alpha}$ for this data, and $\hat{\beta}$ was computed directly using the obtained value of $\hat{\alpha}$ (Table B.6). Figure B.5 shows a comparison between the existing FSPC, the new observed data, and the MLE Weibull approximation. This shows that the MLE Weibull distribution matches the observed data better than the FSPC, and indicates that a higher proportion of crossties will fail sooner than the FSPC would have predicted.

Table B.6: Weibull parameters from the Maximum Likelihood Estimation

Weibull Parameter	Value
α	3.76
β	0.86

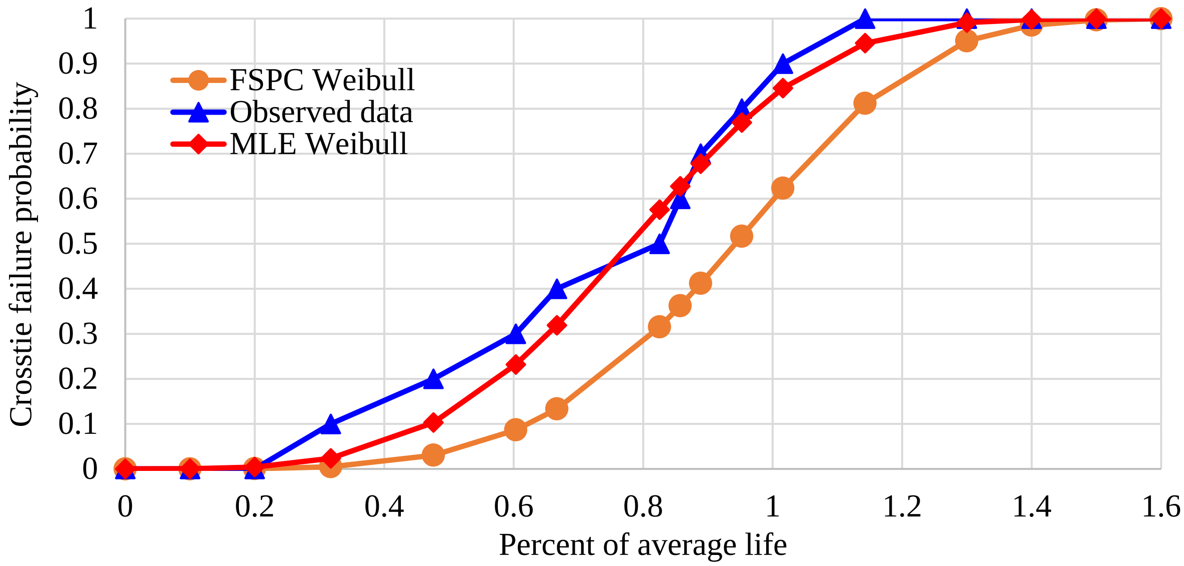

Figure B.5: Comparison between the observed data, the MLE Weibull distribution, and the FSPC

It should be noted that this method will require more precise observations of the crosstie condition to have a better measure of when the crossties fail, but this can be done fairly easily with the cooperation of track inspectors who walk the track several times a week. Also a much larger data set would be needed to adequately approximate the Weibull parameters.

B.8 Conclusions

The FSPC has a wide range of applications for timber crosstie maintenance planning. It can be used to identify approximately when crosstie renewals need to be performed as well as measuring the probability of a slow order being imposed, which can have significant operational impacts.

However, maintenance planning personnel need to be aware that the FSPC may not be accurate in all operating conditions. Therefore, the FSPC needs to be validated under specific circumstances. If necessary the FSPC can either be updated using Bayesian updating, or a new curve can be developed using new data and the MLE method.

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B.10 Sub-appendix

B.10.1 Values used for the least squares regression

$\alpha = 4.56$
$\beta = 1.02$
$\sum residuals$=0.0003937

Table B.7: Least squares regression values

% of life	FSPC	Weibull	diff	f(x)
0		0.00		
0.1		0.00		
0.2		0.00		
0.3		0.00		
0.4		0.01		
0.55	0.05	0.06	0.00	0.46
0.64	0.1	0.11	0.00	0.74
0.74	0.2	0.20	0.00	1.11
0.82	0.3	0.30	0.00	1.40
0.88	0.4	0.40	0.00	1.58
0.94	0.5	0.50	0.00	1.68
1.00	0.6	0.60	0.00	1.67
1.06	0.7	0.69	0.00	1.56
1.14	0.8	0.80	0.00	1.29
1.24	0.9	0.91	0.00	0.81
1.32	0.95	0.96	0.00	0.44
1.40		0.99		
1.50		1.00		
1.60		1.00		

B.10.2 Values used to determine the slow order probability for all crossties being the same age

Table B.8: Slow order probabilities

Year	p(fail)	p(slow order)	0	1	2	3	4	5	6	7	8	9	10	11	Poisson
1	1.33E-07	0	0.999997	3.07E-06	4.5E-12	4.2E-18	2.8E-24	1.42E-30	5.68E-37	1.84E-43	4.91E-50	1.09E-56	2.04E-63	3.21E-70	0
2	3.15E-06	0	0.999928	7.24E-05	2.51E-09	5.52E-14	8.69E-19	1.04E-23	9.81E-29	7.5E-34	4.72E-39	2.47E-44	1.09E-49	4.06E-55	0
3	2E-05	0	0.99954	0.00046	1.01E-07	1.42E-11	1.42E-15	1.08E-19	6.46E-24	3.14E-28	1.25E-32	4.18E-37	1.17E-41	2.77E-46	0
4	7.43E-05	0	0.998293	0.001705	1.39E-06	7.24E-10	2.69E-13	7.59E-17	1.69E-20	3.05E-24	4.53E-28	5.61E-32	5.83E-36	5.12E-40	0
5	0.000205	0	0.995285	0.004704	1.06E-05	1.53E-08	1.57E-11	1.23E-14	7.57E-18	3.78E-21	1.55E-24	5.32E-28	1.53E-31	3.72E-35	0
6	0.000472	0	0.989204	0.01074	5.58E-05	1.84E-07	4.35E-10	7.8E-13	1.11E-15	1.27E-18	1.2E-21	9.41E-25	6.22E-28	3.47E-31	0
7	0.000953	0	0.978313	0.02146	0.000225	1.5E-06	7.17E-09	2.6E-11	7.43E-14	1.72E-16	3.28E-19	5.22E-22	6.97E-25	7.86E-28	0
8	0.001751	0	0.96049	0.038753	0.000748	9.18E-06	8.05E-08	5.37E-10	2.83E-12	1.2E-14	4.22E-17	1.23E-19	3.03E-22	6.29E-25	0
9	0.002995	0	0.933346	0.064478	0.00213	4.48E-05	6.73E-07	7.68E-09	6.92E-11	5.05E-13	3.03E-15	1.52E-17	6.38E-20	2.27E-22	0
10	0.004837	0	0.894463	0.100004	0.005347	0.000182	4.42E-06	8.17E-08	1.19E-09	1.41E-11	1.37E-13	1.11E-15	7.54E-18	4.33E-20	0
11	0.007461	0	0.841763	0.145544	0.012036	0.000633	2.38E-05	6.8E-07	1.53E-08	2.8E-10	4.21E-12	5.27E-14	5.55E-16	4.93E-18	0
12	0.011076	0	0.774015	0.199383	0.024564	0.001926	0.000108	4.59E-06	1.54E-07	4.19E-09	9.4E-11	1.75E-12	2.75E-14	3.64E-16	0
13	0.015917	0	0.691408	0.257205	0.04576	0.005181	0.000419	2.58E-05	1.25E-06	4.91E-08	1.59E-09	4.28E-11	9.69E-13	1.85E-14	0
14	0.022245	1.54321E-14	0.59606	0.311905	0.078059	0.012432	0.001414	0.000122	8.34E-06	4.61E-07	2.1E-08	7.96E-10	2.53E-11	6.81E-13	2.09E-12
15	0.030345	6.03628E-13	0.492261	0.354319	0.121972	0.026719	0.004181	0.000497	4.67E-05	3.55E-06	2.22E-07	1.16E-08	5.07E-10	1.88E-11	8.17E-11
16	0.040517	1.74107E-11	0.386237	0.375133	0.174254	0.051509	0.010876	0.001745	0.000221	2.27E-05	1.91E-06	1.35E-07	7.97E-09	3.98E-10	2.36E-09
17	0.053074	3.89034E-10	0.285279	0.367759	0.226736	0.088958	0.02493	0.00531	0.000893	0.000122	1.36E-05	1.27E-06	9.99E-08	6.61E-09	5.27E-08
18	0.068329	6.84952E-09	0.196356	0.331216	0.267204	0.137177	0.050303	0.014019	0.003084	0.000549	8.06E-05	9.85E-06	1.01E-06	8.77E-08	9.27E-07
19	0.086587	9.62897E-08	0.124551	0.271556	0.283163	0.187897	0.089058	0.032081	0.009123	0.0021	0.000398	6.29E-05	8.35E-06	9.35E-07	1.3E-05
20	0.108131	1.0912E-06	0.071932	0.200585	0.267511	0.227034	0.13763	0.063409	0.023063	0.006791	0.001647	0.000333	5.65E-05	8.09E-06	0.000148
21	0.133208	1.00346E-05	0.037329	0.131944	0.223047	0.239943	0.18437	0.107668	0.049639	0.018526	0.005694	0.001458	0.000314	5.7E-05	0.001358
22	0.162005	7.5197E-05	0.017161	0.076308	0.162274	0.2196	0.21227	0.155941	0.090441	0.042462	0.016418	0.00529	0.001432	0.000327	0.010129
23	0.194639	0.000460288	0.006883	0.038261	0.101715	0.172076	0.207936	0.190964	0.138456	0.081264	0.03928	0.015822	0.005353	0.001529	0.060414
24	0.231131	0.002303664	0.002369	0.016381	0.054167	0.113983	0.171323	0.195707	0.176495	0.128851	0.077468	0.038813	0.016335	0.005803	0.267931
25	0.271392	0.009428821	0.000688	0.005891	0.024137	0.062935	0.117209	0.165901	0.185384	0.167697	0.124928	0.077555	0.040443	0.017803	0.720993
26	0.315204	0.031564061	0.000165	0.001748	0.008853	0.028524	0.065647	0.114824	0.158556	0.177242	0.163165	0.125172	0.080661	0.043878	0.986064
27	0.362213	0.086502588	3.22E-05	0.00042	0.002626	0.010438	0.029641	0.063967	0.108985	0.150316	0.170735	0.161606	0.128491	0.086241	0.999992
28	0.411918	0.194660685	4.98E-06	8.02E-05	0.000618	0.00303	0.010611	0.028243	0.059348	0.100955	0.141426	0.165101	0.161902	0.134022	1
29	0.463682	0.362185487	5.98E-07	1.19E-05	0.000113	0.000684	0.002959	0.00972	0.025211	0.052935	0.091532	0.131892	0.159641	0.163115	1
30	0.516741	0.564493839	5.45E-08	1.34E-06	1.58E-05	0.000118	0.000631	0.002562	0.008218	0.021342	0.045641	0.081339	0.121764	0.153873	1
31	0.570229	0.753131699	3.67E-09	1.12E-07	1.63E-06	1.52E-05	0.000101	0.000508	0.00202	0.00651	0.017275	0.038202	0.070962	0.111273	1
32	0.623214	0.887543304	1.78E-10	6.77E-09	1.23E-07	1.43E-06	1.18E-05	7.41E-05	0.000368	0.001477	0.004886	0.013471	0.031193	0.060975	1
33	0.674742	0.959945315	6.04E-12	2.88E-10	6.58E-09	9.55E-08	9.91E-07	7.81E-06	4.86E-05	0.000245	0.001016	0.003514	0.010204	0.025018	1
34	0.723888	0.989101689	1.4E-13	8.42E-12	2.43E-10	4.46E-09	5.84E-08	5.82E-07	4.58E-06	2.91E-05	0.000153	0.000668	0.002451	0.007593	1
35	0.769809	0.997780141	2.13E-15	1.64E-13	6.02E-12	1.41E-10	2.36E-09	3E-08	3.01E-07	2.44E-06	1.63E-05	9.1E-05	0.000426	0.001684	1
36	0.811794	0.999667542	2.07E-17	2.06E-15	9.76E-14	2.95E-12	6.35E-11	1.04E-09	1.35E-08	1.41E-07	1.22E-06	8.75E-06	5.29E-05	0.000269	1
37	0.849309	0.999963986	1.25E-19	1.62E-17	1E-15	3.96E-14	1.11E-12	2.39E-11	4.04E-10	5.52E-09	6.23E-08	5.85E-07	4.62E-06	3.07E-05	1
38	0.882025	0.999997221	4.48E-22	7.7E-20	6.33E-18	3.31E-16	1.24E-14	3.52E-13	7.9E-12	1.43E-10	2.14E-09	2.67E-08	2.8E-07	2.47E-06	1
39	0.909832	0.999999849	9.25E-25	2.15E-22	2.38E-20	1.68E-18	8.49E-17	3.26E-15	9.86E-14	2.42E-12	4.87E-11	8.2E-10	1.16E-08	1.38E-07	1
40	0.932833	0.999999994	1.06E-27	3.38E-25	5.16E-23	5.02E-21	3.49E-19	1.84E-17	7.67E-16	2.59E-14	7.18E-13	1.66E-11	3.23E-10	5.3E-09	1

B.10.3 Values and VBA code used to determine the slow order probability for multiple crosstie ages

Table B.9: Slow order probabilities

Year	p(slow order)	Slow order
0	0.00	0.00
1	0.00	0.01
2	0.00	0.06
3	0.00	0.31
4	0.00	0.84
5	0.00	1.00
6	0.00	1.00
7	0.00	1.00
8	0.01	1.00

```
Sub sloworder()
Dim i(1 To 5) As Double, k(1 To 5, 1 To 1000000) As Double, imax(1 To 5) As Double, p(1 To
5) As Double
Dim j As Double, y As Double, l As Double, avglife As Double
Dim row As Double, pHold As Double, pTotal As Double, C As Double, alpha As Double, beta
As Double, ties39 As Double
row = 3
C = 9
alpha = Range("alpha")
beta = Range("beta")
avglife = Range("avglife")
ties39 = Range("ties39")

For j = 1 To 5
   imax(j) = Sheets("tie ages").Cells(j + 6, 7)
Next

For y = 1 To 9
   pTotal = 0
   i(1) = 0
   Do
      i(2) = 0
      Do
         i(3) = 0
         Do
            i(4) = 0
            Do
               i(5) = 0
               Do
                  If i(1) + i(2) + i(3) + i(4) + i(5) < 11 Then
```

```
                pHold = 1
                For j = 1 To 5
                    p(j) = 1 - Exp(-1 * ((y + (j - 1) * C) / beta / avglife) ^ alpha)
                    pHold = pHold * WorksheetFunction.Combin(imax(j), i(j)) * p(j) ^ i(j) * _
                    (1 - p(j)) ^ (imax(j) - i(j))
                Next
                pTotal = pTotal + pHold
            End If
            i(5) = i(5) + 1
          Loop Until i(5) > imax(5)
          i(4) = i(4) + 1
        Loop Until i(4) > imax(4)
        i(3) = i(3) + 1
      Loop Until i(3) > imax(3)
      i(2) = i(2) + 1
    Loop Until i(2) > imax(2)
    i(1) = i(1) + 1
  Loop Until i(1) > imax(1)
  Sheets("Slow order risk (complex)").Cells(y + 2, 2) = 1 - pTotal
Next
End Sub
```

B.10.4 Formulation for the Bayesian updating likelihood function

$$
\begin{aligned}
L(\alpha,\beta) = {} & F_T(1) \times \left(1 - F_T(1)\right)^2 \times \left(F_T(10)\right)^2 \times \left(1 - F_T(10)\right) \times F_T(19) \times \left(1 - F_T(19)\right) \\
& \times F_T(37) \times \left(1 - F_T(37)\right) \\
& = \left(1 - \exp\left(-\left(\frac{1}{\beta}\right)^{\alpha}\right)\right) \times \left(1 - \left(1 - \exp\left(-\left(\frac{1}{\beta}\right)^{\alpha}\right)\right)\right)^2 \\
& \times \left(1 - \exp\left(-\left(\frac{10}{\beta}\right)^{\alpha}\right)\right)^2 \times \left(1 - \left(1 - \exp\left(-\left(\frac{10}{\beta}\right)^{\alpha}\right)\right)\right) \\
& \times \left(1 - \exp\left(-\left(\frac{19}{\beta}\right)^{\alpha}\right)\right) \times \left(1 - \left(1 - \exp\left(-\left(\frac{19}{\beta}\right)^{\alpha}\right)\right)\right) \\
& \times \left(1 - \exp\left(-\left(\frac{28}{\beta}\right)^{\alpha}\right)\right) \times \left(1 - \left(1 - \exp\left(-\left(\frac{37}{\beta}\right)^{\alpha}\right)\right)\right) \\
& = \left(1 - \exp\left(-\left(\frac{1}{\beta}\right)^{\alpha}\right)\right) \times \left(1 - \exp\left(-\left(\frac{10}{\beta}\right)^{\alpha}\right)\right)^2 \times \left(1 - \exp\left(-\left(\frac{19}{\beta}\right)^{\alpha}\right)\right) \\
& \times \left(1 - \exp\left(-\left(\frac{28}{\beta}\right)^{\alpha}\right)\right) \times \exp\left(-(2\left(\frac{1}{\beta}\right)^{\alpha} + \left(\frac{10}{\beta}\right)^{\alpha} + \left(\frac{19}{\beta}\right)^{\alpha} + \left(\frac{37}{\beta}\right)^{\alpha}\right)
\end{aligned}
$$

B.10.5 VBA code used for numerical approximation of the Bayesian updating integrals

```
Sub integration()
Dim a As Double, b As Double, t As Double, u As Double  'these are the variables to be used in the integration
Dim Da As Double, Db As Double, Dt As Double 'these are the increments for each variable
Dim aMax As Double, bMax As Double, tMax As Double 'these are the maximum values for the sum since I can't evaluate up to infinity
Dim ia As Double, ib As Double, it As Double  ' these are counting variables
Dim aHat As Double, bHat As Double 'these are the point estimates
Dim a1 As Double, b1 As Double ‘these are the priors
Da = Cells(26, 2)
Db = Cells(27, 2)
Dt = Cells(28, 2)
aMax = Cells(26, 3)
bMax = Cells(27, 3)
tMax = Cells(28, 3)

ia = 0
Do
   ib = 0
   Do
      it = 0
      Do
         a = (ia + 0.5 * Da)
         b = (ib + 0.5 * Db)
         t = (it + 0.5 * Dt)
         u = u + Da * Db * Dt * Exp(-1 * (2 * (1 / b) ^ a + (10 / b) ^ a + (19 / b) ^ a + _
         (37 / b) ^ a + (t/b1)^a1)) * a1 / b1 * (t / b1) ^ (a1 - 1) * (1 - Exp(-1 * (1 / b) ^ a)) * _
         (1 - Exp(-1 * (10 / b) ^ a)) ^ 2 * (1 - Exp(-1 * (19 / b) ^ a)) * _
         (1 - Exp(-1 * (28 / b) ^ a))
         it = it + Dt
      Loop Until it >= tMax
      ib = ib + Db
   Loop Until ib >= tMax
   ia = ia + Da
Loop Until ia >= tMax

u = 1 / u

ia = 0
Do
   ib = 0
   Do
      it = 0
      Do
         a = (ia + 0.5 * Da)
```

```
            b = (ib + 0.5 * Db)
            t = (it + 0.5 * Dt)
            aHat = aHat + a * Da * Db * Dt * u * Exp(-1 * (2 * (1 / b) ^ a + (10 / b) ^ a + _
            (19 / b) ^ a + (37 / b) ^ a +(t/b1)^a1))*a1/b1*(t/b1) ^ (a1 - 1) * (1 - Exp(-1 * (1 / b) ^ a)) _
            * (1 - Exp(-1 * (10 / b) ^ a)) ^ 2 * (1 - Exp(-1 * (19 / b) ^ a)) * (1 - Exp(-1 * (28 / b) ^ a))
            bHat = bHat + b * Da * Db * Dt * u * Exp(-1 * (2 * (1 / b) ^ a + (10 / b) ^ a + _
            (19 / b) ^ a + (37 / b) ^ a + (t/b1)^a1))*a1/b1*(t/b1)^ (a1 - 1) * (1 - Exp(-1 * (1 / b) ^ a)) _
            * (1 - Exp(-1 * (10 / b) ^ a)) ^ 2 * (1 - Exp(-1 * (19 / b) ^ a)) * (1 - Exp(-1 * (28 / b) ^ a))
            it = it + Dt
        Loop Until it >= tMax
        ib = ib + Db
    Loop Until ib >= tMax
    ia = ia + Da
Loop Until ia >= tMax

Cells(30, 2) = u
Cells(31, 2) = aHat
Cells(32, 2) = bHat

End Sub
```

B.10.6 Formulation for the Maximum likelihood function

$$\ln L(\alpha,\beta) \propto \sum_{i=1}^{n} \ln \frac{\alpha}{\beta}\left(\frac{t_i}{\beta}\right)^{\alpha-1} \exp\left(-\left(\frac{t_i}{\beta}\right)^{\alpha}\right)$$

$$\propto \sum_{i=1}^{n} \ln \alpha - \ln \beta + \alpha \ln t_i - \ln t_i - \alpha \ln \beta + \ln \beta - \left(\frac{t_i}{\beta}\right)^{\alpha}$$

$$\propto n \times \ln \alpha - n \times \ln \beta + \alpha \sum_{i=1}^{n} \ln t_i - \sum_{i=1}^{n} \ln t_i - n \times \alpha \times \ln \beta + n \ln \beta$$

$$- \beta^{-\alpha} \sum_{i=1}^{n} {t_i}^{\alpha} \propto n \times \ln \alpha + \alpha \sum_{i=1}^{n} \ln t_i - \sum_{i=1}^{n} \ln t_i - n \times \alpha * \ln \beta - \beta^{-\alpha} \sum_{i=1}^{n} {t_i}^{\alpha}$$

APPENDIX C.

CROSSTIE LIFE-CYCLE COST SENSITIVITY ANALYSIS VALUES

To perform the sensitivity analysis in Chapter 4, the timber crosstie life-cycle cost and concrete crosstie life-cycle cost was computed for both the lower and upper bounds for each parameter with all the others being kept at their base values. The ratio for each was computed and the arc elasticity was computed (Tables C.1 and C.2). The parameters were then sorted by the difference between their upper and lower bound elasticities.

Table C.1: No alternate route sensitivity values

	T/C Min ratio	T/C Max ratio	Lower bound elasticity	Upper bound elasticity	Range
Possession time	1.04	1.05	0.04	0.05	0.01
Idle fuel cost	1.00	1.02	-0.01	0.01	0.02
Route length	1.03	1.01	0.02	0.00	0.02
Running fuel cost	1.00	1.03	-0.02	0.02	0.03
Setup/tear down time	1.00	1.03	-0.01	0.03	0.05
Average train weight	0.96	1.04	-0.06	0.03	0.09
Timber tie life	1.01	0.91	0.00	-0.11	0.11
Timber renewal threshold	1.05	1.02	0.15	0.03	0.13
Concrete accident cost	1.06	0.94	0.05	-0.08	0.13
Concrete renewal speed	0.92	1.03	-0.13	0.03	0.16
Concrete tamping cost	1.04	0.89	0.03	-0.13	0.16
Timber accident cost	0.98	1.15	-0.04	0.15	0.19
Timber tie cost	0.81	1.03	-0.23	0.02	0.25
Timber tamping cost	0.86	1.16	-0.16	0.15	0.31
Concrete renewal cycle	0.92	1.04	-0.28	0.08	0.35
Concrete tamping speed	1.19	0.88	0.22	-0.15	0.37
Delay cost less fuel	0.74	1.17	-0.30	0.18	0.48
Timber accident rate	0.77	1.24	-0.25	0.24	0.48
Concrete accident rate	1.24	0.76	0.25	-0.26	0.51
Concrete tamping frequency	0.65	1.12	-0.41	0.12	0.53
Timber tamping speed	0.73	1.28	-0.34	0.33	0.67
Percent double track	1.20	0.73	0.29	-0.45	0.75
Trains per day	0.65	1.40	-0.40	0.43	0.83
Discount rate	1.44	0.74	0.50	-0.33	0.83
Timber tamping frequency	1.48	0.66	0.62	-0.47	1.08
Concrete tie spacing	0.86	1.13	-0.61	0.49	1.10
Timber renewal speed	1.73	0.86	0.92	-0.20	1.12
Concrete tie cost	1.99	0.66	1.08	-0.39	1.46

Table C.2 Alternate route sensitivity values

	T/C min ratio	T/C Max ratio	Lower bound elasticity	Upper bound elasticity	Range
Siding/crossover spacing	0.88	0.89	0.00	0.00	0.01
Possession time	0.91	0.90	0.04	0.02	0.02
Average train weight	0.87	0.89	-0.02	0.01	0.03
Setup/tear down time	0.88	0.90	-0.02	0.04	0.05
Timber renewal threshold	0.92	0.90	0.17	0.06	0.11
Concrete renewal speed	0.82	0.90	-0.11	0.03	0.13
Timber tie life	0.88	0.77	0.00	-0.15	0.15
Concrete accident cost	0.93	0.80	0.06	-0.10	0.16
Alt. route double track %	0.91	0.83	0.06	-0.10	0.16
Running fuel cost	0.81	0.95	-0.09	0.09	0.18
Concrete tamping cost	0.91	0.76	0.04	-0.16	0.19
Timber accident rate	0.79	0.98	-0.11	0.11	0.22
Concrete accident rate	0.97	0.76	0.11	-0.14	0.25
Timber accident cost	0.84	1.05	-0.05	0.22	0.27
Delay cost less fuel	0.75	0.99	-0.17	0.14	0.31
Concrete tamping speed	1.01	0.79	0.18	-0.13	0.31
Timber tie cost	0.64	0.92	-0.31	0.05	0.35
Route length	0.75	1.03	-0.17	0.19	0.36
Alt. route trains per day	0.84	1.06	-0.07	0.31	0.37
Concrete renewal cycle	0.79	0.90	-0.33	0.06	0.40
Timber tamping cost	0.70	1.07	-0.22	0.21	0.44
Alt. route class	0.96	0.69	0.13	-0.33	0.47
Track class	0.67	0.96	-0.36	0.13	0.49
Concrete tamping frequency	0.59	0.97	-0.38	0.11	0.49
Trains per day	0.64	1.08	-0.31	0.25	0.56
Reroute ratio	0.69	0.96	-0.45	0.18	0.62
Timber tamping speed	0.64	1.11	-0.33	0.32	0.65
Percent double track	1.02	0.65	0.26	-0.42	0.68
Discount rate	1.38	0.61	0.67	-0.37	1.04
Timber tamping frequency	1.34	0.54	0.69	-0.52	1.20
Timber renewal speed	1.67	0.75	1.15	-0.20	1.35
Concrete tie spacing	0.72	1.02	-0.73	0.62	1.36
Concrete tie cost	2.28	0.54	1.75	-0.44	2.19

APPENDIX D.

CROSSTIE COST COMPARISONS

For the case study, each the life-cycle costs for renewal, derailments, slow orders, and surfacing were calculated for both timber and concrete crossties on each line.

Table D.1: Life-cycle costs for Line A ($ millions)

	Timber				Concrete			
	Direct	Delay	Network	Total	Direct	Delay	Network	Total
Renewal	52.41	17.89	0.00	70.30	150.80	10.86	0.00	161.66
Derailment	6.59	17.14	0.00	23.73	8.02	12.56	0.00	20.58
Slow order	0.33	0.13	0.00	0.46	0.00	0.00	0.00	0.00
Surfacing	84.37	165.97	0.00	250.34	8.18	45.75	0.00	53.93
Total	143.69	201.14	0.00	344.83	167.00	69.17	0.00	236.17

Table D.2: Life-cycle costs for Line B ($ millions)

	Timber				Concrete			
	Direct	Delay	Network	Total	Direct	Delay	Network	Total
Renewal	104.81	0.04	0.69	105.54	301.59	0.03	0.42	302.04
Derailment	17.57	0.82	2.66	21.05	21.40	0.60	1.95	23.95
Slow order	0.67	0.35	0.00	1.01	0.00	0.00	0.00	0.00
Surfacing	168.74	0.41	6.39	175.54	16.36	0.11	1.76	18.23
Total	291.78	1.62	9.75	303.15	339.35	0.74	4.13	344.22

Table D.3: Life-cycle costs for Line C ($ millions)

	Timber				Concrete			
	Direct	Delay	Network	Total	Direct	Delay	Network	Total
Renewal	88.08	1.70	0.00	89.77	253.44	1.03	0.00	254.47
Derailment	19.76	143.41	0.00	163.17	24.07	105.06	0.00	129.13
Slow order	0.56	0.66	0.00	1.22	0.00	0.00	0.00	0.00
Surfacing	141.79	15.73	0.00	157.53	13.75	4.34	0.00	18.09
Total	250.20	161.49	0.00	411.69	291.26	110.43	0.00	401.69

Table D.4: Life-cycle costs for Line D ($ millions)

	Timber				Concrete			
	Direct	Delay	Network	Total	Direct	Delay	Network	Total
Renewal	88.08	2.39	0.00	90.46	253.44	1.45	0.00	254.89
Derailment	21.96	178.56	0.00	200.53	26.75	130.82	0.00	157.57
Slow order	0.56	0.73	0.00	1.29	0.00	0.00	0.00	0.00
Surfacing	141.79	22.13	0.00	163.92	13.75	6.10	0.00	19.85
Total	252.39	203.81	0.00	456.20	293.93	138.37	0.00	432.30

APPENDIX E.

MODIFIED WEBSTER DERIVATIONS

Equation 5.1 is based on the basice equation for a line, y = mx+b

The period before T_M, when maintenance is being performed, has no traffic, so it is zero at all points.

The normal operations curve begins at the origin and has a known slope, so the equation is straightforward.

$$q_t = N_N t$$

When the slow order is in place, $T_M \leq t \leq (T_E + T_M)$, the slope is known, so only the intercept needs to be solved for. To simplify the calculations, the origin will be shifted to $(0,T_M)$, which negates the need to explicitly calculate b

$$q_t = \gamma_{SO} N_N (t - T_M)$$

The recovery period, $(T_E + T_M) \leq t \leq T_Z$, has a known slope, so shifting the origin to the beginning of the curve ($t = T_E+T_M$, $q_t = \gamma_{SO}N_NT_E$), will once again negate the need to explicitly calculate the y-intercept.

$$q_t - \gamma_{SO} N_N (T_E + T_M - T_M) = \gamma_Z N_N \big(t - (T_E + T_M)\big)$$

$$q_t = \gamma_Z N_N \big(t - (T_E + T_M)\big) + \gamma_{SO} N_N T_E$$

$$= \gamma_Z N_N (t - T_E - T_M) + \gamma_{SO} N_N T_E$$

$$= N_N (\gamma_Z (t - T_E - T_M) + \gamma_{SO} T_E)$$

The time T_Z can then be calculated as the intersction between the normal operations and recovery lines.

$$N_N T_Z = N_N(\gamma_Z(T_Z - T_E - T_M) + \gamma_{SO} T_E)$$

$$T_Z = \gamma_Z(T_Z - T_E - T_M) + \gamma_{SO} T_E$$

$$= \gamma_Z T_Z - \gamma_Z T_E - \gamma_Z T_M + \gamma_{SO} T_E$$

$$\gamma_Z T_Z - T_Z - = \gamma_Z T_E + \gamma_Z T_M - \gamma_{SO} T_E$$

$$T_Z(\gamma_Z - 1) = \gamma_Z(T_E + T_M) - \gamma_{SO} T_E$$

$$T_Z = \frac{\gamma_Z(T_E + T_M) - \gamma_{SO} T_E}{(\gamma_Z - 1)}$$

Equation 5.7 is based on the difference in the area of two triangles

$$T_D = \frac{T_B Q_Z}{2} - \frac{(T_B - T_M)Q_S}{2}$$

$$= \frac{1}{2}(T_B Q_Z - (T_B - T_M)Q_S)$$

Equation 5.8 is found by finding the x-intercept of the recovery curve

From Equation 5.1

$$\begin{aligned}
q_T &= N_N(\gamma_Z(T_B - T_E - T_M) + \gamma_{SO} T_E) \\
&= 0 \\
0 &= N_N(\gamma_Z(T_B - T_E - T_M) + \gamma_{SO} T_E) \\
&= \gamma_Z(T_B - T_E - T_M) + \gamma_{SO} T_E \\
-\gamma_{SO} T_E &= \gamma_Z(T_B - T_E - T_M) \\
-\gamma_{SO} T_E &= \gamma_Z T_B - \gamma_Z T_E - \gamma_Z T_M \\
\gamma_Z T_B &= \gamma_Z T_E + \gamma_Z T_M - \gamma_{SO} T_E \\
T_B &= T_E + T_M - \frac{\gamma_{SO}}{\gamma_Z} T_E \\
&= T_M + T_E\left(1 - \frac{\gamma_{SO}}{\gamma_Z}\right)
\end{aligned}$$

Equation 5.9 is the point T_Z on the normal operations curve and is self-explanatory.

Similarly Equation 5.10 is the slow order curve evaluated at (T_E+T_M, $\gamma_{SO}N_NT_E$)

$$
\begin{aligned}
Q_S &= \gamma_{SO}N_N(T_E + T_M - T_M) \\
&= \gamma_{SO}N_NT_E
\end{aligned}
$$

APPENDIX F.

OPERATIONAL IMPACT SENSITIVITY ANALYSIS VALUES

To conduct the sensitivity analysis in Chapter 5, each of the input parameters were varied to minimum and maximum values while all other parameters were kept at the average values (Table F.1). The delay for each scenario was then computed using the methodology in Chapter 5.

Table F.1: Raw input and output values from the operational impact sensitivity analysis

	Inputs			Output (train-hours)		
	Minimum	Average	Maximum	Minimum	Average	Maximum
Track outage time, T_M (hours)	0	12	24	4583.29	7328.85	10506.41
Slow order duration, T_E (hours)	0	120	240	216.00	7328.85	23608.29
Route length, L_R (mile)	2[1]	101[1]	200[1]	14011.44	7328.85	4738.31
Individual slow order length, L_{SO} (mile)	0.01[1]	0.505[1]	1[1]	7111.95	7328.85	7541.78
Average train length, L_T (mile)	0.5[1]	1[1]	1.5[1]	7109.74	7328.85	7543.91
Normal train velocity, V_N (mph)	30[1]	55[1]	80[1]	4765.12	7328.85	9435.01
Slow order train velocity, V_{SO} (mph)	10[1]	20[1]	30[1]	8311.14	7328.85	6981.52
Number of slow orders, N_{SO}	0	3	6	1728.00	7328.85	11216.91
Additional acceleration and deceleration time T_{AD} (hours)	0.1	0.3	0.5	4277.06	7328.85	9756.97
Trains per hour, N_N	0.1	1.05	2	697.99	7328.85	13959.72
Normal capacity utilization, R_N	0.4	0.65	0.9	5404.71	7328.85	18873.74

1. 1 mile = 1.61 km

The arc elasticity was then computed for each case using the variance of the minimum and maximum parameter value delay output and sorted according to the difference between the maximum and minimum elasticities (Table F.2).

Table F.2: Delay differences and arc elasticity calculations for the operational impact sensitivity analysis

	Difference from Average		Arc elasticity		
	Minimum	Maximum	Minimum	Maximum	Range
Track outage time, T_M (hours)	-2745.56	3177.56	-0.375	0.434	0.808
Slow order duration, T_E (hours)	-7112.85	16279.44	-0.971	2.221	3.192
Route length, L_R (mile [km])	6682.58	-2590.54	0.930	-0.361	1.291
Individual slow order length, L_{SO} (mile [km])	-216.90	212.92	-0.030	0.030	0.060
Average train length, L_T (mile [km])	-219.11	215.05	-0.060	0.059	0.118
Normal train velocity, V_N (mph [km/h])	-2563.74	2106.15	-0.770	0.632	1.402
Slow order train velocity, V_{SO} (mph [km/h])	982.29	-347.33	0.268	-0.095	0.363
Number of slow orders, N_{SO}	-5600.85	3888.06	-0.764	0.531	1.295
Additional acceleration and deceleration time T_{AD} (hours)	-3051.79	2428.12	-0.625	0.497	1.122
Trains per hour, N_N	-6630.87	6630.87	-1.000	1.000	2.000
Normal capacity utilization, R_N	-1924.15	11544.88	-0.683	4.096	4.778

APPENDIX G.

BALLAST SLOW ORDER WEIBULL REGRESSION

To find a ballast defect prediction model, data from the 2015 INFORMS Railway Applications Section Problem Solving Completion (RAS PSC) was used. The competition was to predict if a yellow defect would have developed into a red (FRA) defect after a specified amount of time. Although maintenance events were not indicated in the data, a more robust dataset could not be obtained. Capital maintenance events were assumed to have occurred if an inspection found a red defect (a red inspection) and the subsequent inspection did not find a defect. If an inspection was performed and no defect was found, I classified it as a green inspection. Maintenance was assumed to occur halfway between the initial red inspection and subsequent green inspection.

The RAS PSC data was processed to find sets of inspections where the first was red, the second was green, and the third could be any result. The number of days and accumulated tonnage between the assumed maintenance and the red inspection was calculated. Normalized tonnage was also computed by dividing the accumulated tonnage by the number of days between the inspections. The RAS PSC data were randomly divided into training and testing datasets containing 80% and 20% of the data, respectively. Several combinations of explanatory variables were evaluated, and most had statistically significant results (Table G.1). If a coefficient cell is blank, it was not tested in that case. All models were applied to the testing dataset and their accuracy was calculated by counting the number of correct results, and dividing by the total number of records. A result was counted as correct if the Weibull probability was greater than 0.5 and the record had a red defect, or the probability was less than 0.5 and the record did not have a red defect. The Weibull shape parameter is the inverse of the scale, and the scale parameter was calculated as shown in Chapter 6. Even though some models were not statistically significant, they were all reasonably accurate (Table G.1).

Although the model that does not include any explanatory variables was not the most accurate, it only varied from the most accurate by less than one-tenth of a percent. Given the limited dataset and assumptions, it was determined that the basic model without explanatory variables was sufficient for demonstration purposes. It was retrained against the complete dataset to provide the most accurate model. If additional data can be acquired, further analysis can be performed to develop a more robust model.

Table G.1: Weibull regression results

Case	Scale	Intercept	Coefficients							Chi-squared probability	Accuracy
			Class_5	Class_4	Class_3	Speed	Curve	Tons	Norm_Tons		
1	0.54	7.73	0.97	0.84	-0.60	-0.01	-2.79	0.01	-9.04	1.00	0.955
2	0.43	6.75				0.00	1.29	0.01	-3.78	0.00	0.955
3	0.40	7.38	-0.66	-0.78	-0.87		2.02	0.01	-3.44	0.00	0.956
4	0.53	9.47	4.31	3.47	0.33	-0.08		0.01	-10.32	1.00	0.955
5	0.90	3.25	-8.13	-6.39	-3.39	0.20	3.37		2.11	2.50E-10	0.954
6	0.47	6.54	-2.68	-2.43	-1.50	0.04	2.71	0.01		0.00	0.956
7	0.43	6.81					2.06	0.01	-3.76	0.00	0.955
8	0.43	6.75				0.00		0.01	-3.81	0.00	0.955
9	0.91	6.23				0.04	3.54		2.29	3.40E-06	0.955
10	0.50	6.85				-0.01	7.67	0.01		0.00	0.955
11	0.40	7.38	-0.66	-0.78	-0.87			0.01	-3.44	0.00	0.956
12	0.91	8.17	0.28	-0.08	-1.10		8.16		4.68	1.50E-04	0.955
13	0.45	7.45	-1.06	-1.21	-0.97		7.68	0.01		0.00	0.956
14	0.90	3.25	-8.13	-6.39	-3.39	0.20			2.11	7.00E-11	0.954
15	0.47	6.54	-2.68	-2.43	-1.50	0.04		0.01		0.00	0.956
16	0.90	3.35	-7.60	-5.88	-3.19	0.19	3.29			4.40E-10	0.954
17	0.33	6.62						0.02	-5.74	1.00	0.955
18	0.91	7.91					8.15		6.65	1.90E-03	0.955
19	0.52	6.58					8.00	0.01		0.00	0.954
20	0.91	6.23				0.04			2.29	7.80E-07	0.955
21	0.50	6.85				-0.01		0.01		0.00	0.955
22	0.91	6.20				0.05	3.48			1.90E-06	0.955
23	0.91	8.17	0.28	-0.08	-1.10				4.67	5.60E-05	0.955
24	0.45	7.45	-1.06	-1.21	-0.97			0.01		0.00	0.956
25	0.91	8.20	1.11	0.77	-0.89		8.01			3.70E-04	0.955
26	0.90	3.35	-7.60	-5.88	-3.19	0.19				1.10E-10	0.954
27	0.91	8.20	1.11	0.77	-0.89					1.20E-04	0.955
28	0.91	6.20				0.05				2.80E-07	0.955
29	0.92	9.12					7.95			9.50E-01	0.955
30	0.52	6.58						0.01		0.00	0.954
31	0.91	7.91							6.64	4.00E-04	0.955
32	0.92	9.12									0.955

APPENDIX H.

RISK ANALYSIS COMPONENT COSTS

The four maintenance schedule alternatives in the case study in Chapter 7 were evaluated using the methodology described in that chapter to compute the component and total costs for each alternative (Table H.1).

Table H.1: Cost components for the risk analysis case study

	Maintenance direct cost	Maintenance delay cost	Acute disruption cost	Slow Order cost	Total
Base	$44,038,542	$139,167,379	$905,858	$140,779,151	$324,890,930
Alternative 1a	$49,913,916	$153,783,045	$905,839	$130,294,736	$334,897,536
Alternative 1b	$43,871,265	$132,511,400	$905,864	$143,338,912	$320,627,441
Alternative 2	$42,986,536	$128,059,671	$905,858	$140,781,153	$312,733,219

APPENDIX I.

MAINTENANCE AGGREGATION ON LONG WORK WINDOW DIRECT COST MODIFICATIONS

Since 24-hour work window values were not given in the original Burns & Franke (2005) report, they had to be calculated using their approach. Unless otherwise indicated all values come from Burns & Franke (2005). The basic calculation follows this form:

$$cost\ per\ mile = \frac{5280\ \times \frac{cost}{day}}{Production\ rate\ \times \frac{Production\ hours}{shift}}$$

The production rate was given in the report based on the authors' experience. Production hours per shift were calculated using

$$\frac{Production\ hours}{shift} = Productivity\ \times\ actual\ production\ hours$$

$$\begin{aligned} &actual\ production\ hours \\ &\qquad = possession\ hours - (travel, start, \&\ clear\ time) \\ &\qquad - (lost\ production\ time\ due\ to\ meal\ \&\ coffee\ breaks) \end{aligned}$$

Meals and coffee breaks were assumed to be 30 and 15 minutes respectively. Travel, start, & clear time was taken as 1.5 hours per shift.

The cost/day consisted of the cost of crews and equipment over the shift and was calculated based on the authors' experience on an 8-hour shift. Equipment use time was based on the amount of time the equipment was in use, which is approximately the production time minus the breaks but isn't explicitly calculated in the report.

$$\begin{aligned} typcial\ \frac{cost}{day} &= (8\ hour\ labor\ cost)\frac{paid\ hours\ per\ day}{8} \\ &+ (8\ hour\ equipment\ cost)\frac{equipment\ use\ hours}{8} \end{aligned}$$

The exception to this was ballast cleaning that used the following equation and seems to be based on fixed and variable costs

$$\frac{Ballast\ cleaning\ cost}{day} = (8\ hour\ labor\ cost)\frac{paid\ hours\ per\ day}{8} + (production\ hours) \times production\ rate \times 2 + 1000$$

The number of possessions required per mile was calculated using the production rate, production hours per shift, and a conversion factor based on the authors' experience.

$$required\ number\ of\ possessions\ per\ mile = 5280 \times \frac{Adjustment\ factor}{production\ rate\ \frac{production\ hours}{shift}}$$

As mentioned in Chapters 7 and 8, the tie replacement and undercutting costs and required number of windows were modified to include surfacing since that would be required for both activities. These were found by simply adding the values for crosstie replacement and ballast cleaning and surfacing. Actual values used are provided in the tables below. Where applicable values were converted to 2015 dollars using a factor of 1.136 (United States Census Bureau 2016).

Table I.1: Division of work window hours

	Work window length		
Value	7.5 hours	24 hours	7 days
Paid hours per day	10	24	24
Possession hours	7.5	24	168
Number of coffee breaks per day	1	4	4
Number of meal breaks	1	2	2
Equipment use hours per day	9.5	22	22
Actual production hours per shift	5.25	20.5	152.5
Productivity	0.95	0.85	0.85
Production hours per shift	4.99	17.4	129.6
Production hours per day	4.99	17.4	18.5

Table I.2: Track maintenance costs

	Rail replace	Tie replace	Ballast cleaning	Surfacing
General values				
Production Rate (ft/hr)	1,000	1,500	1,200	4,000
8 hour labor cost ($)	4,000	3,200	2,000	1,500
8 hour equipment cost ($)	4,000	5,000	6,000	1,500
Adjustment factor	1.5	1.5	1	1.25
Materials cost ($)	172,636[1]	29,600[2]	108,000[3]	13,500[3]
7.5-hour windows				
Possessions per mile	1.59	1.06	0.88	0.33
Cost per day ($)	9,750	9,938	15,470	3,688
Cost per mile ($)	10,322	7,014	13,648	968
2015 Cost per mile ($)	11,726	7,968	15,504	1,100
Total cost per mile ($) with materials	184,362	37,568	123,504	14,600
24-hour windows				
Possessions per mile	0.45	0.30	0.25	0.09
Cost per day ($)	23,000	23,350	48,820	8,625
Cost per mile ($)	6969	4717	12328	653
2015 Cost per mile ($)	7,917	5,359	14,005	742
Total cost per mile ($) with materials	180,553	34,959	122,005	14,242
7-day windows				
Possessions per mile	0.061	0.041	0.034	0.013
Cost per day ($)				
Cost per mile ($)	6,558	4,439	12,223	615
2015 Cost per mile ($)	7,450	5,043	13,885	699
Total cost per mile ($) with materials	180,086	34,642	121,885	14,199

1. (ACW Railway Company 2015)
2. (Burns 1989)
3. Using costs from ACW Railway Company (2015) and amounts from Chrismer (1988)

I.1 References

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APPENDIX J.

AGGREGATION ON LONG WORK WINDOWS CASE STUDY COSTS

The component and total costs for the case study from Chapter 8 were computed using the methodology in that chapter (Table J.1).

Table J.1: Output from the Chapter 8 case study

		Maintenance direct cost	Maintenance delay cost	Acute disruption costs	Slow Order costs	Total
Baseline	Traditional	$73,974,722	$245,101,822	$1,013,943	$262,891,821	$582,982,308
No Detour	Agg. - Same year	$73,167,490	$212,830,673	$1,013,943	$262,891,821	$549,903,927
	Agg. - First year	$71,226,222	$166,275,375	$1,013,943	$262,891,452	$501,406,992
	Agg. - Mid. Year	$68,290,108	$153,376,721	$966,169	$277,461,779	$500,094,777
	Agg. - Last year	$66,674,503	$152,848,417	$1,057,266	$278,225,087	$498,805,273
Detour	Agg. - Same year	$73,067,490	$143,283,584	$1,013,943	$262,891,821	$480,256,838
	Agg. - First year	$71,107,717	$54,351,185	$1,013,943	$262,891,452	$389,364,297
	Agg. - Mid. year	$68,167,258	$56,343,922	$966,169	$277,461,779	$402,939,128
	Agg. - Last year	$66,559,101	$48,741,150	$1,057,266	$278,225,087	$394,582,604

APPENDIX K.

SIMULATED ANNEALING MODEL CODE

The following R code was developed to create the initial maintenance schedules and run the simulated annealing. The imported files contain tables with the annual tonnage, route lengths, detour lengths, double track indicator, capacity utilization, and time since previous maintenance for rail, crossties, and ballast.

```
timestamp()
starttime<-Sys.time()
library(xlsx)

TDelay<-function(NN,RN,TM,NSO,TE,TAD,VN,VSO,LR,LSO,LT){

   gz<-1/RN

  if(VSO>0){
   TN<-LR/VN
   TSO<-min(TN+NSO*((LSO+LT)*(1/VSO-1/VN)+TAD),LR/VSO)
   gso<-TN/TSO

  }else{
   gso<-1
  }

  TB<-TM+TE*(1-gso/gz)
  QZ<-NN*(gso*TE-gz*(TM+TE))/(1-gz)
  QS<-gso*NN*TE

  return(max(.5*(TB*QZ-(TB-TM)*QS),0))
}

#data import------------------------
#activities<-3
#years<-50
#routes<-3

NAjk<-data.matrix(read.xlsx("C:/Users/alovett2/Box Sync/Maint Opt/Maint Opt data
import.xlsx",sheetName =  "NAjk"))#data.matrix(read_excel("~/Box Sync/Maint Opt/Maint
comparison - current.xlsm", sheet = "NAjk"))#array(1:years*routes, dim = c(years,routes))*0+30
#MGT/year#
```

```
LNjk<-data.matrix(read.xlsx("C:/Users/alovett2/Box Sync/Maint Opt/Maint Opt data
import.xlsx",sheetName =  "LNjk"))#data.matrix(read_excel("~/Box Sync/Maint Opt/Maint
comparison - current.xlsm", sheet = "LNjk"))#NAjk*0+100 #route length#
LLjk<-data.matrix(read.xlsx("C:/Users/alovett2/Box Sync/Maint Opt/Maint Opt data
import.xlsx",sheetName =  "LLjk"))#data.matrix(read_excel("~/Box Sync/Maint Opt/Maint
comparison - current.xlsm", sheet = "LLjk"))#NAjk*0+200 #MGT/year#
VLjk<-data.matrix(read.xlsx("C:/Users/alovett2/Box Sync/Maint Opt/Maint Opt data
import.xlsx",sheetName =  "VLjk"))#data.matrix(read_excel("~/Box Sync/Maint Opt/Maint
comparison - current.xlsm", sheet = "VLjk"))#NAjk*0+40 #MGT/year#NAjk*0+40
#MGT/year#
djk<-data.matrix(read.xlsx("C:/Users/alovett2/Box Sync/Maint Opt/Maint Opt data
import.xlsx",sheetName =  "djk")) #data.matrix(read_excel("~/Box Sync/Maint Opt/Maint
comparison - current.xlsm", sheet = "djk"))#binary to indicate if there is double track on the
route#NAjk*0+1#
RNjk<-data.matrix(read.xlsx("C:/Users/alovett2/Box Sync/Maint Opt/Maint Opt data
import.xlsx",sheetName =  "RNjk"))#data.matrix(read_excel("~/Box Sync/Maint Opt/Maint
comparison - current.xlsm", sheet = "RNjk"))#route utilization#NAjk*0+.65 #
Yi0k<-t(data.matrix(read.xlsx("C:/Users/alovett2/Box Sync/Maint Opt/Maint Opt data
import.xlsx",sheetName =  "Yi0k")))#t(data.matrix(read_excel("~/Box Sync/Maint Opt/Maint
comparison - current.xlsm", sheet = "Yi0k")))#years since the maintenance was performed as of
year 0(array(1:routes*activities,dim = c(activities,routes))*0+1)*c(20,9,4) #

ncjk<-c(6,6,6,4,1) #assume 20" tie spacing, 850 ties replaced every 9 years, assume this break
down won't change even if the ties are being replace more frequently

#index information----
imaint<-1:3 #types of maintenance
wwindow<-1:3 #types of windows

jyear<-1:(dim(NAjk)[1]) #years in analysis period
kroute<-1:dim(NAjk)[2] #routes
ccohort<-1:length(ncjk) #5 age groups of ties, but should probably import the actual number of
cohorts

#parameters----
#maybe updated some of these becuase of variations between lines
RI<-.0961 #% discount rate from STB
#CF<-130.76 #cost per hour for 3 flaggers
CGjprime<-1000#$ per activity movement
NRail<-273 #number of rail sections per mile from Orringer 1990
Lambda<-0.014 #from Orringer
theta<-10 #MGT min inspection interval from Orringer
dN<-15#MGT based on the inspection opt paper
TAD<-.2 #additional acceleration and deceleration for each slow order
LSO<-.1#miles that are slow ordered
CB<-1127 # $ per defect
```

```
PXRail<-0.0084 #proportion of broken rails that result in a derailment
NEij<-4 #number of jobs of type i can be completed in year j

CXRail<-616263*1.65 #rail break derailment cost
VS<-10 #mph speed trains will season the track at
NS<-0.2 #MGT to season the track
S1<-19.5206 #sogin parameter
S2<-19.149 #sogin parameter
k<-0.0471 #sogin parameter
CP<- 2000 #detour planning cost
VNjk<-40 #mph normal route speed
T2k<-30 #average life of a crosstie on route k, could also import this if we decide it should
change
LTjk<-1 #average train length
CDjk<-950 #$/train hour based on the Lovett et al 2017 (train delay costing paper)
CTjk<-.002 #millage $/ton-mile
CKjk<-46.78 #additional crew member cost for a detour
NT<-6987#tons per train based on AAR AC1RR
TBD<-5 #hours to repair rail break
TXD<-24 #hours to recover from derailment
fjk<-23-8 #maximum allowable failed ties, anymore and there will be an FRA defect. class 2 or 3
track with curves less than 2 degrees. Could import this if there are different track classes in the
routes
CBudget<-1E9 #annual budget

CJiw<-array(c(184000,52000,138000,181000,49000,136000, 180000,49000,136000), dim =
c(max(imaint),max(wwindow)),dimnames = list(c("Rail","Crossties","Ballast"),c("7.5 hr","24
hr","7 day")))# per mile cost to perform maintenance
CSOi<-c(859,285,1200) #direct cost to repair one defect
TMw<-c(7.5,24,168)#window lengths
CSw<-c(15000,14000,14000) #cost per mile to surface
QSw<-c(.33,.09,.0014)#windows required to surface 1 mile
QJiw<-array(c(1.59,1.39,1.21,.45,.39,.35,.061,.054, .047), dim =
c(max(imaint),max(wwindow)),dimnames = list(c("Rail","Crossties","Ballast"),c("7.5 hr","24
hr","7 day")))# per mile cost to perform maintenance
TEi<-c(24,4*24,3*24) #slow order duration, this could also vary by line
VSOi<-c(30,25,25) #mph slow order for each defect type
alphai<-c(3.1,4.5606500420751,1/0.9193001) #weibull parameters
betai<-c(2150,1.02128074524307,exp(9.089459)) #Weibull parameters
TCik<-c(20,9,4) #normal renewal cycles for each component
TIi<-c(4380,168,168) #inspection interval in hours

NNjk<-NAjk*1000000/NT/365/24 #trains per hour
TBjk<-TDelay(NNjk,RNjk,TBD,0,0,0,40,0,LNjk,0,LTjk)#based on 5 hours to maintain a rail
break
```

```
TXjk<-TDelay(NNjk,RNjk,TXD,0,0,0,40,0,LNjk,0,LTjk)#based on 24 hours to recover from a derailment
#TSjk<-365*24/NAjk*NS #time to season the track

TSJijk<-array(1:length(jyear)*max(kroute)*max(imaint), dim =
c(max(imaint),length(jyear),max(kroute)),dimnames =
list(c("Rail","Crossties","Ballast"),jyear,kroute))*0
for(ii in imaint){ #determining the seasoning period for each route and year
  if(ii==1){
    TSJijk[ii,,]<-0
  } else{
    for(kk in kroute){
      TSJijk[ii,,kk]<-365*24/NAjk[,kk]*NS#TSjk
    }
  }
}

CX3ijk<-
c(0,.0410677618069815*(361102*1.65+TXjk*CDjk),0.137577002053388*(403091*1.65+TXjk
*CDjk))*.11 #rates may change between routes
CX2ijk<-
c(0,.080814312152992*(131980*1.65+TXjk*CDjk),0.155459592843923*(200068*1.65+TXjk*
CDjk))*.22

yc0k<-array(1:length(ccohort)*length(kroute),dim = c(length(ccohort),length(kroute))) #should
import the actual amounts, and determine the number of cohorts from this imported value

for(kk in kroute){
  yc0k[1,kk]<-Yi0k[2,kk]# the most recent cohort was installed in the last renewal
  for(cc in ccohort[-1]){ #all others are installed in 9 year intervals
    yc0k[cc,kk]<-yc0k[cc-1,kk]+TCik[2]
  }
}

ycjk<-array(1:max(ccohort)*length(jyear)*max(kroute), dim =
c(max(ccohort),length(jyear),max(kroute)))*0 # cohort ages through time, which will depend on
when maintenance is performed
yl<-0:100 # this is a dummy variable for use in populating pyk
pyk<-array(1:length(yl)*max(kroute), dim = c(length(yl),max(kroute)))*0 #variable to store the
probability of failure in each route for 50 years, so it doesn't have to be calculated everytime

for(kk in kroute){
  pyk[,kk]<-pweibull(yl,alphai[2],betai[2]*T2k)
}
cntr<-1 #this process will need to change if there are different track classes represented
Fjk1<-ccohort
```

```
temp<-expand.grid(0:ncjk[1],0:ncjk[2],0:ncjk[3],0:ncjk[4],0:ncjk[5]) # using the assumed
cohorts above (ncjk)
for(ii in 1:dim(temp)[1]){
  if(sum(temp[ii,])>fjk){
    Fjk1[cntr]<-ii
    cntr<-cntr+1
  }
}
Fk<-temp[Fjk1,]

#intermediate vals-----
Ctotaljk<-array(1:length(jyear)*max(kroute), dim = c(length(jyear),max(kroute)))*0 #total cost
on each route in each year
Ctotalk<-kroute*0
CMjk<-array(1:length(jyear)*max(kroute), dim = c(length(jyear),max(kroute)))*0 #maintenance
cost per mile
CSOjk<-array(1:length(jyear)*max(kroute), dim = c(length(jyear),max(kroute)))*0 #slow order
cost per mile
CXjk<-array(1:length(jyear)*max(kroute), dim = c(length(jyear),max(kroute)))*0 #accute
disruption cost per mile
QWjk<-array(1:length(jyear)*max(kroute), dim = c(length(jyear),max(kroute)))*0 #maintenance
windows per mile
TMjk<-array(1:length(jyear)*max(kroute), dim = c(length(jyear),max(kroute)))*0 #maintenance
window length
TSjk<-array(1:length(jyear)*max(kroute), dim = c(length(jyear),max(kroute)))*0 #surfacing
time when blitz is used
LMjk<-array(1:length(jyear)*max(kroute), dim = c(length(jyear),max(kroute)))*0 #length of
track maintained per window
RBjk<-array(1:length(jyear)*max(kroute), dim = c(length(jyear),max(kroute)))*0 #annual rail
break rate
yijk<-array(1:length(jyear)*max(kroute)*max(imaint), dim =
c(max(imaint),length(jyear),max(kroute)),dimnames =
list(c("Rail","Crossties","Ballast"),jyear,kroute))*0
RSOijk<-array(1:length(jyear)*max(kroute)*max(imaint), dim =
c(max(imaint),length(jyear),max(kroute)),dimnames =
list(c("Rail","Crossties","Ballast"),jyear,kroute))*0
CSOijk<-array(1:length(jyear)*max(kroute)*max(imaint), dim =
c(max(imaint),length(jyear),max(kroute)),dimnames =
list(c("Rail","Crossties","Ballast"),jyear,kroute))*0
CSODijk<-array(1:length(jyear)*max(kroute)*max(imaint), dim =
c(max(imaint),length(jyear),max(kroute)),dimnames =
list(c("Rail","Crossties","Ballast"),jyear,kroute))*0
CXijk<-array(1:length(jyear)*max(kroute)*max(imaint), dim =
c(max(imaint),length(jyear),max(kroute)),dimnames =
list(c("Rail","Crossties","Ballast"),jyear,kroute))*0
```

```
CDMjk<-array(1:length(jyear)*max(kroute), dim = c(length(jyear),max(kroute))) #total
maintenance delay cost

CGj<-jyear

PSOijk<-array(1:length(jyear)*max(kroute)*max(imaint), dim =
c(max(imaint),length(jyear),max(kroute)),dimnames =
list(c("Rail","Crossties","Ballast"),jyear,kroute))*0
pHold<-matrix(1:(length(ccohort)*dim(Fk)[1]),ncol = length(ccohort))*0 #tie group by
occurance holds the probability of observign the condition in question
pHold1<-matrix(1:(length(ccohort)*dim(Fk)[1]),ncol = length(ccohort))*0 #tie group by
outcome for the next year
pHoldsum<-(1:dim(Fk)[1])*0 #hold the probability fo each event
pHoldsum1<-(1:dim(Fk)[1])*0 #hold the probability fo each event

#Variables----
#can to import the preexisting schedule

# only have to deal with xijk since the base case will be no detour and only 7.5 hour windows
xijk<-array(1:length(jyear)*max(kroute)*max(imaint), dim =
c(max(imaint),length(jyear),max(kroute)),dimnames =
list(c("Rail","Crossties","Ballast"),jyear,kroute))*0 #starting plan for selected maintenance
activities
ajkw<-array(1:length(jyear)*max(kroute)*max(wwindow), dim =
c(length(jyear),max(kroute),max(wwindow)),dimnames = list(jyear,kroute,c("7.5 hr","24 hr","7
day")))*0 #starting condition for windows selected
bjk<-array(1:length(jyear)*max(kroute), dim = c(length(jyear),max(kroute)),dimnames =
list(jyear,kroute))*0#+1 #if a detour is selected

#xx<-expand.grid(0:1,0:1,0:1)
#jj1<-0
#kk<-1
#jj<-0
ajkw[,,1]<-1 #everything is one 7.5 hour windows except when there is aggregation
for(kk in kroute){
  for (jj in jyear){
#    ifelse(jj1+1>8,jj1<-1,jj1<-jj1+1)
    for(ii in imaint){
      if((Yi0k[ii,kk]+jj-1)/TCik[ii]==round((Yi0k[ii,kk]+jj-1)/TCik[ii])){
        xijk[ii,jj,kk]<-1
      }
      #xijk[ii,jj,kk]<-xx[jj1,ii]
    }
    if(sum(xijk[,jj,kk])>1){
      ajkw[jj,kk,1]<-0
      ajkw[jj,kk,2]<-1
```

```
    }
  }
}

#ajkw[jj,2,2]<-1
#ajkw[jj,3,3]<-1
#bjk[jj,3]<-1
#ajkw[jj,2,1]<-0
#ajkw[jj,3,1]<-0

#Sim anneal-------
T<-1e9#initial temperature
alfa<-.85 #how quickly it cools
Eil<-jyear #holder for the costs
cntr<-2 #iterations of the annealing process
EBest<-1E100
Eil<-array(c(EBest,EBest),dim = c(1,2)) #holds the options
NumSame<-5
Tmin<-.5

#objectives----
repeat{

  CDMjk<-CDMjk*0
  Ctotalk<-Ctotalk*0
  Ctotal<-0

  for (jj in jyear){
    for (kk in kroute){
      #Maintenance costs#####
      if(ajkw[jj,kk,1]==0 & xijk[1,jj,kk]==1){ #if we are blitzing and rail is being replaced
        QWjk[jj,kk]<-sum(ajkw[jj,kk,]*QJiw[1,]) #rail is the longest
      } else if (ajkw[jj,kk,1]==0 & xijk[1,jj,kk]==0 & xijk[2,jj,kk]==1){ #if we are blitzing and
rail isn't being replaced, but ties are
        QWjk[jj,kk]<-sum(ajkw[jj,kk,]*QJiw[2,]) #ties are the longest
      } else { #everything else just sum up everything that happens and remove one surfacing if
necessary
        for (ww in wwindow){
          if(ajkw[jj,kk,ww]==1){
            QWjk[jj,kk]<-sum(xijk[,jj,kk]*QJiw[,ww])-xijk[2,jj,kk]*xijk[3,jj,kk]*QSw[ww]
          }
        }
      }
      TMjk[jj,kk]<-sum(ajkw[jj,kk,]*TMw)
      CGj[jj]<-sum(xijk[,jj,])*CGjprime
```

```
    for (ww in wwindow){
      if(ajkw[jj,kk,ww]==1){ #if the window type ww is used then sum up the applicable costs
and remove a surfacing if necessary
        CMjk[jj,kk]<-sum(CJiw[,ww]*xijk[,jj,kk])-xijk[2,jj,kk]*xijk[3,jj,kk]*CSw[ww]
      }
    }
  }
  CMjk[jj,]<-CMjk[jj,]*LNjk[jj,]*(1+djk[jj,]) #converting from per mile to total costs

  Nij<-0 #this is to check the resource constraint
  for(ii in imaint){
    Nij<-Nij+ifelse(sum(xijk[ii])>NEij,1,0)
  }

  if((sum(CMjk[jj,])+CGj[jj]<=CBudget) & Nij==0){
  #this is where we would check for the budget constraint if the budget is exceeded then we
don't carry through with the plan and pick another

    for (kk in kroute){

    #Initializing----
      for(ii in imaint){ #this loop gives the years since maintenance
        if(xijk[ii,jj,kk]==0){
          if(jj!=1){
            yijk[ii,jj,kk]<-yijk[ii,jj-1,kk]+1
          }else{
            yijk[ii,jj,kk]<-Yi0k[ii,kk]
          }
        }else{
          yijk[ii,jj,kk]<-0
        }
      }

      if(jj==1){#this loop gives the cohort ages
        ycjk[1,jj,kk]<-yijk[2,jj,kk]
        for(cc in ccohort[-1]){
          ycjk[cc,jj,kk]<-ycjk[cc-1,jj,kk]+TCik[2]
        }
      }else {
        if(xijk[2,jj,kk]==0){
          ycjk[,jj,kk]<-ycjk[,jj-1,kk]+1
        }else{
          ycjk[1,jj,kk]<-0
          ycjk[-1,jj,kk]<-ycjk[-length(ccohort),jj-1,kk]+1
        }
      }
```

```
#Slow order costs----
  RSOijk[1,jj,kk]<-NRail*(pweibull((yijk[1,jj,kk]+1)*NAjk[jj,kk],alphai[1],betai[1])-
pweibull(yijk[1,jj,kk]*NAjk[jj,kk],alphai[1],betai[1]))/
    ((Lambda*(dN-theta)+1))
  RSOijk[3,jj,kk]<-5280/200*(pweibull((yijk[3,jj,kk]+1)*365,alphai[3],betai[3]))

  #tie slow orders
  for(ff in 1:dim(Fk)[1]){
    for(cc in ccohort){
      pHold[ff,cc]<-dbinom(Fk[ff,cc],ncjk[cc],pyk[ycjk[cc,jj,kk]+1])#
      pHold1[ff,cc]<-dbinom(Fk[ff,cc],ncjk[cc],pyk[ycjk[cc,jj,kk]+2])
    }
    pHoldsum[ff]<-prod(pHold[ff,])
    pHoldsum1[ff]<-prod(pHold1[ff,])
  }
  RSOijk[2,jj,kk]<-5280/39*(sum(pHoldsum1)-sum(pHoldsum))
  for(ii in imaint){
    CSOijk[ii,jj,kk]<-RSOijk[ii,jj,kk]*CSOi[ii]
    CSODijk[ii,jj,kk]<-
TDelay(NNjk[jj,kk],RNjk[jj,kk],0,TIi[ii]*RSOijk[ii,jj,kk]/24/365*LNjk[jj,kk],TEi[ii],TAD,VNj
k,VSOi[ii],LNjk[jj,kk],LSO,LTjk)*
      CDjk/TIi[ii]*365*24
  }
  CSOjk[jj,kk]<-sum(CSOijk[,jj,kk]*LNjk[jj,kk],CSODijk[,jj,kk])*(1+djk[jj,kk])
#Acute disruption costs----
  RBjk[jj,kk]<-NRail*Lambda*(dN-
theta)*(pweibull((yijk[1,jj,kk]+1)*NAjk[jj,kk],alphai[1],betai[1])-

pweibull(yijk[1,jj,kk]*NAjk[jj,kk],alphai[1],betai[1]))/((Lambda*(dN-theta)+1))
  CXijk[1,jj,kk]<-RBjk[jj,kk]*(TBjk*CDjk+CB+PXRail*(CXRail+CDjk*TXjk))
  for(ii in imaint[-1]){
    PSOijk[ii,jj,kk]<-min(LSO*RSOijk[ii,jj,kk]/24/365*TEi[ii],1)
    CXijk[ii,jj,kk]<-NAjk[jj,kk]/1000*(PSOijk[ii,jj,kk]*CX2ijk[ii]+(1-
PSOijk[ii,jj,kk])*CX3ijk[ii])
  }
  CXjk[jj,kk]<-sum(CXijk[,jj,kk])*LNjk[jj,kk]*(1+djk[jj,kk])
#Delay costs-----------
  LMjk[jj,kk]<-ifelse(QWjk[jj,kk]>0,1/QWjk[jj,kk],0)
  TSjk[jj,kk]<-ifelse(xijk[2,jj,kk]+xijk[3,jj,kk]>0,TSJijk[2,jj,kk],0)
  if(ajkw[jj,kk,1]==1 & bjk[jj,kk]==0){ #if it is not aggregated and not blitzed
    if(djk[jj,kk]==0){ #if it isn't double track
      for(ii in imaint){
        CDMjk[jj,kk]<-QJiw[ii,1]*xijk[ii,jj,kk]*
          TDelay(NNjk[jj,kk],RNjk[jj,kk],TMjk[jj,kk]*(1-bjk[jj,kk])*(1-
djk[jj,kk]),1,TSJijk[ii,jj,kk],TAD,VNjk,VS,LNjk[jj,kk],1/QJiw[ii,1],LTjk)+CDMjk[jj,kk]
```

```
          }
          CDMjk[jj,kk]<-CDMjk[jj,kk]-
xijk[2,jj,kk]*xijk[3,jj,kk]*QSw[1]*TDelay(NNjk[jj,kk],RNjk[jj,kk],TMjk[jj,kk],1,TSjk[jj,kk],T
AD,VNjk,VS,LNjk[jj,kk],1/QSw[1],LTjk)
        } else{ # if it is double track
          CDMjk[jj,kk]<-
QWjk[jj,kk]*(1+djk[jj,kk])*(TMjk[jj,kk]*NNjk[jj,kk]*LNjk[jj,kk]/240/60*(S1-S2*(LNjk[jj,kk]-
LMjk[jj,kk])/LNjk[jj,kk])*exp(24*k*NNjk[jj,kk])+

TDelay(NNjk[jj,kk],RNjk[jj,kk],0,1,TSjk[jj,kk],TAD,VNjk,VS,LNjk[jj,kk],LMjk[jj,kk],LTjk))
        }
        CDMjk[jj,kk]<-CDjk*CDMjk[jj,kk]
       }

      if(ajkw[jj,kk,1]!=1){
        if(bjk[jj,kk]==0){ #if a detour isn't used
          if(djk[jj,kk]==0){ #if it isn't double track
            CDMjk[jj,kk]<-
TDelay(NNjk[jj,kk],RNjk[jj,kk],TMjk[jj,kk],1,TSjk[jj,kk],TAD,VNjk,VS,LNjk[jj,kk],LMjk[jj,k
k],LTjk)
          } else{ #if it is double track
            CDMjk[jj,kk]<-(1+djk[jj,kk])*(TMjk[jj,kk]*NNjk[jj,kk]*LNjk[jj,kk]/240/60*(S1-
S2*(LNjk[jj,kk]-LMjk[jj,kk])/LNjk[jj,kk])*exp(24*k*NNjk[jj,kk])+

TDelay(NNjk[jj,kk],RNjk[jj,kk],0,1,TSjk[jj,kk],TAD,VNjk,VS,LNjk[jj,kk],LMjk[jj,kk],LTjk))
          }
          CDMjk[jj,kk]<-CDjk*CDMjk[jj,kk]
        } else{ #if a detour is used
          CDMjk[jj,kk]<-
CP+LLjk[jj,kk]*(CTjk*NAjk[jj,kk]*1000000/365/24*TMjk[jj,kk]+CKjk/VLjk[jj,kk])+CDjk*(L
Ljk[jj,kk]/VLjk[jj,kk]-LNjk[jj,kk]/VNjk)+

CDjk*(1+djk[jj,kk])*TDelay(NNjk[jj,kk],RNjk[jj,kk],0,1,TSjk[jj,kk],TAD,VNjk,VS,LNjk[jj,kk]
,LMjk[jj,kk],LTjk)
        }
        CDMjk[jj,kk]<-QWjk[jj,kk]*CDMjk[jj,kk]
       }
      CDMjk[jj,kk]<-CDMjk[jj,kk]*LNjk[jj,kk]
     } #end of kk
     Ctotaljk[jj,]<-(CMjk[jj,]+CSOjk[jj,]+CXjk[jj,]+CDMjk[jj,])

     Ctotal<-sum(Ctotaljk[jj,],CGj[jj])/(1+RI)^(jj-1)+Ctotal
    } else {
     Ctotal<-0
     break
    }
```

```
  } #end of jj

  for(kk in kroute){
    for(jj in jyear){
      Ctotalk[kk]<-Ctotaljk[jj,kk]/(1+RI)^(jj-1)+Ctotalk[kk]
    }
  }

  if(Ctotal>0){ #if the solution met the constraints, if it didn't then it will just change the best
again
    Eil<-rbind(Eil,c(sum(Ctotal),EBest))
    #Sim anneal-accept/reject----
    if(Eil[cntr,1]<min(Eil[,1])){
      xBestest<-xBest
      aBestest<-ajkw
      bBestest<-bjk
      Ctotalkbest<-Ctotalk
    }
    if(exp(-(Eil[cntr,1]-EBest)/T)>=runif(1)){
      EBest<-Eil[cntr,1]
      Eil[cntr,2]<-Eil[cntr,1]
      xBest<-xijk
      aBest<-ajkw
      bBest<-bjk
    }
    if(cntr>NumSame){ #if there have been more than a given number with the same result
      if((max(Eil[c((cntr-NumSame):cntr),2]) == min(Eil[c((cntr-NumSame):cntr),2]) &
T<Tmin)){ #if there have been more than a given number with the same result and the temp is
below the min value
        break #end the search
      }
    }
    cntr<-cntr+1
    T<-T*alfa
  }

  #Sim anneal - change one thing---------
  xijk<-xBest #change the current best
  ajkw<-aBest
  bjk<-bBest

  xabrand<-sample(2,1) #random variable to change, 1 is move a maintenance activity, 2 is add a
detour
  krand<-sample(kroute,1) #pick a random route to change

  #jrand<-sample(jyear,1) #pick a random year to change
```

```
 if(xabrand==1){ # if the maintenance activity has been selected
   irand<-sample(imaint,1) #pick a random activity
   xirand<-sample(sum(xijk[irand,,krand]),1) # pick an occurance of that activity
   audrand<-sample(2,1) #pick if it should be moved up or down
   xcnt<-0
   jrand<-0
   for(jj in jyear){#this counts to find the selected occurance of maintenance type i
     if(xijk[irand,jj,krand]==1){
       xcnt<-xcnt+1
       if(xcnt==xirand){
         jrand<-jj
         break
       }
     }
   }

   xijk[irand,jrand,krand]<-0#turn it off in the selected year
   if(sum(xijk[,jrand,krand])<2){ #if there is only one activity being performed in that year, it
should go back to being 7.5 hr windows
     ajkw[jrand,krand,1]<-1
     ajkw[jrand,krand,2]<-0
     ajkw[jrand,krand,3]<-0
     bjk[jrand,krand]<-0
   }

   if(audrand==1){#move one year earlier
     if(jrand>1){ #if the original activity took place in the first year, then it will just fall off the
planning period
       xijk[irand,jrand-1,krand]<-1
       ajkw[jrand-1,krand,]<-0
       if(sum(xijk[,jrand-1,krand])>1){
         if(bjk[jrand-1,krand]==1){
           ajkw[jrand-1,krand,3]<-1
         } else{
           ajkw[jrand-1,krand,2]<-1
         }
       } else{
         ajkw[jrand-1,krand,1]<-1
         bjk[jrand-1,krand]<-0
       }
     }

     if(xirand==sum(xijk[irand,,krand]) & jrand==length(jyear)-(TCik[irand]-1)){#add new one
at the end if necessary to match the cycle, this will only happen when the activity was originally
scheduled one less than the cycle from the last year
```

```
        xijk[irand,length(jyear),krand]<-1
        ajkw[length(jyear),krand,]<-0
        if(sum(xijk[,length(jyear),krand])>1){
          if(bjk[length(jyear),krand]==1){
            ajkw[length(jyear),krand,3]<-1
          } else{
            ajkw[length(jyear),krand,2]<-1
          }
        } else{
          ajkw[length(jyear),krand,1]<-1
          bjk[length(jyear),krand]<-0
        }
      }
    } else{ #move one year later
      if(jrand<length(jyear)){ #if the original activity took place in the last year, then it will just
fall off the planning period
        xijk[irand,jrand+1,krand]<-1
        ajkw[jrand+1,krand,]<-0
        if(sum(xijk[,jrand+1,krand])>1){
          if(bjk[jrand+1,krand]==1){
            ajkw[jrand+1,krand,3]<-1
          } else{
            ajkw[jrand+1,krand,2]<-1
          }
        }else{
          bjk[jrand+1,krand]<-0
          ajkw[jrand+1,krand,1]<-1
        }
      }
    }
  }else{#if the detour was selected
    bjkrand<-sample(length(jyear)-sum(ajkw[,krand,1]),1) #pick a random occurance of
aggregation to add a detour to
    xcnt<-0
    jrand<-0
    for(jj in jyear){#this counts to find the selected occurance of aggregation
      if(ajkw[jj,krand,1]==0){
        xcnt<-xcnt+1
        if(xcnt==bjkrand){
          jrand<-jj
          break
        }
      }
    }
    bjk[jrand,krand]<-abs(bjk[jrand,krand]-1) #change it from on to off or vise versa
    ajkw[jrand,krand,]<-0
```

```
    if(sum(xijk[,jrand,krand])>1){
      if(bjk[jrand,krand]==1){
        ajkw[jrand,krand,3]<-1
      } else{
        ajkw[jrand,krand,2]<-1
      }
    } else{
      ajkw[jrand,krand,1]<-1
      bjk[jrand,krand]<-0
    }
  }
}

timestamp()
print(Sys.time()-starttime)
print(min(Eil[,1]))
print(EBest)
#print(proc.time())
#print(xBest)
#print(aBest)
#print(bBest)
```

APPENDIX L.

SIMULATED ANNEALING PARAMETER TEST RESULTS

The code in Appendix K was run with different values of the initial T and α to determine the optimal values (Table L.1). This data is summarized in Chapter 9.

Table L.1: Simulated annealing parameter test results

Initial T	α	Minimum Cost	Percent improvement	Time elapsed (min)	Percent improvement per minute
1E+06	0.85	1,183,514,065	4.05%	3.267	1.24%
1E+07	0.85	1,203,672,507	2.42%	3.925	0.62%
1E+08	0.85	1,225,926,394	0.62%	4.334	0.14%
1E+09	0.85	1,200,800,972	2.65%	4.794	0.55%
1E+10	0.85	1,185,200,750	3.92%	5.301	0.74%
1E+11	0.85	1,142,993,094	7.34%	5.883	1.25%
1E+12	0.85	1,200,337,508	2.69%	6.314	0.43%
1E+13	0.85	1,116,023,117	9.53%	6.711	1.42%
1E+14	0.85	1,189,790,996	3.55%	7.023	0.50%
1E+06	0.90	1,189,977,513	3.53%	4.849	0.73%
1E+07	0.90	1,194,067,012	3.20%	5.452	0.59%
1E+08	0.90	1,190,825,935	3.46%	6.203	0.56%
1E+09	0.90	1,157,837,932	6.14%	7.066	0.87%
1E+10	0.90	1,157,445,419	6.17%	7.807	0.79%
1E+11	0.90	1,148,780,370	6.87%	8.429	0.82%
1E+12	0.90	1,159,142,162	6.03%	9.379	0.64%
1E+13	0.90	1,217,943,879	1.26%	9.819	0.13%
1E+14	0.90	1,203,897,043	2.40%	10.578	0.23%
1E+06	0.95	1,185,527,236	3.89%	9.995	0.39%
1E+06	0.85	1,197,873,348	2.89%	3.459	0.84%
1E+06	0.85	1,192,404,910	3.33%	3.549	0.94%
1E+07	0.85	1,181,994,600	4.18%	4.037	1.03%
1E+07	0.85	1,194,374,160	3.17%	3.967	0.80%
1E+08	0.85	1,184,739,769	3.96%	4.764	0.83%
1E+08	0.85	1,176,852,056	4.59%	4.136	1.11%
1E+09	0.85	1,180,352,084	4.31%	4.657	0.93%
1E+09	0.85	1,195,204,579	3.11%	4.680	0.66%
1E+10	0.85	1,157,139,620	6.19%	5.141	1.20%
1E+10	0.85	1,130,903,428	8.32%	5.110	1.63%
1E+11	0.85	1,122,924,600	8.97%	5.686	1.58%

Initial T	α	Minimum Cost	Percent improvement	Time elapsed (min)	Percent improvement per minute
1E+11	0.85	1,183,714,087	4.04%	5.634	0.72%
1E+12	0.85	1,095,926,396	11.16%	6.089	1.83%
1E+12	0.85	1,200,989,489	2.64%	6.202	0.43%
1E+13	0.85	1,125,648,788	8.75%	6.748	1.30%
1E+13	0.85	1,229,265,795	0.35%	6.865	0.05%
1E+14	0.85	1,194,595,730	3.16%	6.998	0.45%
1E+14	0.85	1,233,529,944	0.00%	7.508	0.00%
1E+06	0.90	1,193,369,492	3.26%	5.107	0.64%
1E+06	0.90	1,197,834,033	2.89%	5.171	0.56%
1E+07	0.90	1,197,122,088	2.95%	5.959	0.50%
1E+07	0.90	1,194,939,533	3.13%	5.712	0.55%
1E+08	0.90	1,197,401,719	2.93%	6.617	0.44%
1E+08	0.90	1,200,768,942	2.66%	6.420	0.41%
1E+09	0.90	1,142,147,841	7.41%	7.052	1.05%
1E+09	0.90	1,166,049,593	5.47%	6.985	0.78%
1E+10	0.90	1,159,194,679	6.03%	7.976	0.76%
1E+10	0.90	1,219,044,691	1.17%	7.866	0.15%
1E+11	0.90	1,161,507,905	5.84%	8.554	0.68%
1E+11	0.90	1,175,619,272	4.69%	8.945	0.52%
1E+12	0.90	1,150,815,055	6.71%	9.368	0.72%
1E+12	0.90	1,150,619,067	6.72%	9.268	0.73%
1E+13	0.90	1,214,944,172	1.51%	9.864	0.15%
1E+13	0.90	1,219,154,447	1.17%	10.228	0.11%
1E+14	0.90	1,200,861,915	2.65%	11.022	0.24%
1E+14	0.90	1,214,132,646	1.57%	10.940	0.14%
1E+06	0.95	1,185,527,236	3.89%	9.947	0.39%
1E+06	0.95	1,185,527,236	3.89%	9.625	0.40%
1E+07	0.95	1,185,527,236	3.89%	11.141	0.35%
1E+07	0.95	1,164,018,093	5.64%	11.767	0.48%
1E+07	0.95	1,173,096,984	4.90%	11.409	0.43%
1E+08	0.95	1,160,560,006	5.92%	12.846	0.46%
1E+08	0.95	1,143,561,870	7.29%	13.911	0.52%
1E+08	0.95	1,188,723,885	3.63%	13.081	0.28%
1E+09	0.95	1,161,167,296	5.87%	14.384	0.41%
1E+09	0.95	1,155,950,054	6.29%	14.279	0.44%
1E+09	0.95	1,155,413,711	6.33%	14.510	0.44%
1E+10	0.95	1,176,473,708	4.63%	15.947	0.29%
1E+10	0.95	1,155,363,504	6.34%	15.636	0.41%
1E+10	0.95	1,124,231,736	8.86%	15.743	0.56%
1E+11	0.95	1,163,417,370	5.68%	17.312	0.33%
1E+11	0.95	1,150,389,488	6.74%	16.769	0.40%

Initial T	α	Minimum Cost	Percent improvement	Time elapsed (min)	Percent improvement per minute
1E+11	0.95	1,119,574,745	9.24%	18.906	0.49%
1E+12	0.95	1,190,671,667	3.47%	20.515	0.17%
1E+12	0.95	1,184,590,279	3.97%	20.764	0.19%
1E+12	0.95	1,166,363,166	5.45%	20.789	0.26%
1E+13	0.95	1,155,312,742	6.34%	22.089	0.29%
1E+13	0.95	1,223,004,344	0.85%	21.494	0.04%
1E+13	0.95	1,221,373,241	0.99%	21.261	0.05%
1E+14	0.95	1,205,829,160	2.25%	22.596	0.10%
1E+14	0.95	1,158,854,320	6.05%	22.225	0.27%
1E+14	0.95	1,215,337,755	1.47%	21.900	0.07%
1E+06	0.99	1,185,527,236	3.89%	50.110	0.08%
1E+07	0.99	1,100,620,490	10.77%	55.855	0.19%
1E+07	0.99	1,138,318,266	7.72%	57.381	0.13%
1E+08	0.99	1,058,923,648	14.16%	66.344	0.21%
1E+08	0.99	1,119,816,028	9.22%	65.937	0.14%
1E+06	0.99	1,125,709,026	8.74%	49.720	0.18%
1E+09	0.99	1,199,784,087	2.74%	73.887	0.04%
1E+10	0.99	1,212,165,185	1.73%	80.713	0.02%
1E+06	0.85	1,193,476,638	3.25%	3.123	1.04%
1E+09	0.99	1,223,889,300	0.78%	71.774	0.01%
1E+06	0.99	1,181,634,585	4.21%	49.635	0.08%
1E+07	0.99	1,082,620,257	12.23%	56.618	0.22%
1E+08	0.99	1,137,808,756	7.76%	64.758	0.12%
1E+09	0.99	1,156,865,768	6.22%	74.026	0.08%
1E+10	0.99	1,209,492,730	1.95%	80.036	0.02%
1E+10	0.99	1,232,099,326	0.12%	79.469	0.00%
1E+07	0.85	1,159,206,568	6.03%	3.668	1.64%
1E+08	0.85	1,193,935,942	3.21%	4.133	0.78%
1E+09	0.85	1,177,674,190	4.53%	4.641	0.98%
1E+10	0.85	1,200,284,954	2.70%	5.087	0.53%
1E+11	0.85	1,196,379,974	3.01%	5.624	0.54%
1E+11	0.99	1,219,154,447	1.17%	86.228	0.01%
1E+12	0.85	1,214,635,520	1.53%	6.308	0.24%
1E+13	0.85	1,122,162,043	9.03%	6.363	1.42%
1E+12	0.99	1,214,944,172	1.51%	93.501	0.02%
1E+13	0.99	1,209,280,214	1.97%	106.745	0.02%
1E+14	0.85	1,219,119,405	1.17%	7.364	0.16%
1E+14	0.90	1,167,034,000	5.39%	10.944	0.49%
1E+13	0.90	1,220,730,962	1.04%	10.274	0.10%
1E+14	0.99	1,210,380,926	1.88%	109.486	0.02%
1E+12	0.90	1,145,839,596	7.11%	9.153	0.78%

Initial T	α	Minimum Cost	Percent improvement	Time elapsed (min)	Percent improvement per minute
1E+11	0.90	1,158,997,875	6.04%	8.377	0.72%
1E+10	0.90	1,180,761,485	4.28%	7.930	0.54%
1E+09	0.90	1,140,501,451	7.54%	7.221	1.04%
1E+08	0.90	1,207,307,194	2.13%	6.618	0.32%
1E+07	0.90	1,192,566,292	3.32%	5.672	0.59%
1E+06	0.90	1,166,504,991	5.43%	4.935	1.10%
1E+06	0.95	1,178,169,017	4.49%	9.963	0.45%
1E+07	0.95	1,182,464,148	4.14%	11.534	0.36%
1E+08	0.95	1,116,853,477	9.46%	13.184	0.72%
1E+09	0.95	1,176,087,233	4.66%	14.773	0.32%
1E+10	0.95	1,146,703,868	7.04%	16.478	0.43%
1E+11	0.95	1,127,053,291	8.63%	17.544	0.49%
1E+12	0.95	1,211,472,384	1.79%	19.128	0.09%
1E+13	0.95	1,143,107,551	7.33%	20.695	0.35%
1E+14	0.95	1,225,453,275	0.65%	22.218	0.03%
1E+14	0.99	1,212,765,077	1.68%	109.795	0.02%
1E+13	0.99	1,187,946,965	3.70%	104.660	0.04%
1E+11	0.99	1,216,685,910	1.37%	89.086	0.02%
1E+11	0.99	1,166,886,294	5.40%	87.317	0.06%
1E+12	0.99	1,189,999,448	3.53%	97.510	0.04%
1E+12	0.99	1,178,422,026	4.47%	98.719	0.05%
1E+13	0.99	1,218,291,701	1.24%	106.510	0.01%
1E+14	0.99	1,224,584,817	0.73%	110.798	0.01%
1E+06	0.99	1,138,327,961	7.72%	50.991	0.15%
1E+07	0.99	1,167,637,714	5.34%	58.684	0.09%
1E+08	0.99	1,127,952,101	8.56%	67.211	0.13%
1E+09	0.99	1,151,094,523	6.68%	74.311	0.09%
1E+10	0.99	1,214,570,550	1.54%	82.807	0.02%
1E+11	0.99	1,219,128,597	1.17%	87.161	0.01%
1E+12	0.99	1,214,068,913	1.58%	94.561	0.02%
1E+13	0.99	1,206,107,238	2.22%	103.831	0.02%
1E+14	0.99	1,217,626,455	1.29%	109.906	0.01%
1E+06	0.85	1,189,103,535	3.60%	3.351	1.07%
1E+07	0.85	1,175,614,553	4.70%	3.939	1.19%
1E+08	0.85	1,139,389,740	7.63%	4.345	1.76%
1E+09	0.85	1,176,189,411	4.65%	5.489	0.85%
1E+10	0.85	1,211,174,737	1.81%	5.649	0.32%
1E+11	0.85	1,128,657,576	8.50%	5.757	1.48%
1E+12	0.85	1,165,555,345	5.51%	6.107	0.90%
1E+13	0.85	1,202,274,401	2.53%	6.702	0.38%
1E+14	0.85	1,174,929,685	4.75%	6.989	0.68%

Initial T	α	Minimum Cost	Percent improvement	Time elapsed (min)	Percent improvement per minute
1E+14	0.90	1,185,924,418	3.86%	10.835	0.36%
1E+13	0.90	1,181,956,092	4.18%	10.149	0.41%
1E+12	0.90	1,219,158,156	1.17%	9.386	0.12%
1E+11	0.90	1,196,119,594	3.03%	9.492	0.32%
1E+10	0.90	1,160,142,986	5.95%	8.648	0.69%
1E+09	0.90	1,175,380,548	4.71%	7.592	0.62%
1E+08	0.90	1,196,593,960	2.99%	6.255	0.48%
1E+07	0.90	1,183,201,083	4.08%	5.522	0.74%
1E+06	0.90	1,194,249,002	3.18%	4.743	0.67%
1E+06	0.95	1,188,769,246	3.63%	9.622	0.38%
1E+07	0.95	1,131,145,649	8.30%	11.101	0.75%
1E+08	0.95	1,126,767,145	8.66%	12.609	0.69%
1E+09	0.95	1,077,864,514	12.62%	14.158	0.89%
1E+10	0.95	1,160,103,578	5.95%	15.658	0.38%
1E+11	0.95	1,214,252,365	1.56%	17.052	0.09%
1E+12	0.95	1,219,849,964	1.11%	18.590	0.06%
1E+13	0.95	1,183,839,901	4.03%	20.237	0.20%
1E+14	0.95	1,218,711,694	1.20%	22.181	0.05%
1E+06	0.99	1,122,673,699	8.99%	50.634	0.18%
1E+07	0.99	1,119,099,977	9.28%	58.155	0.16%
1E+08	0.99	1,089,294,092	11.69%	67.083	0.17%
1E+09	0.99	1,178,187,503	4.49%	78.068	0.06%
1E+10	0.99	1,233,529,944	0.00%	83.650	0.00%
1E+11	0.99	1,222,170,866	0.92%	89.536	0.01%
1E+12	0.99	1,186,071,056	3.85%	94.449	0.04%
1E+13	0.99	1,187,107,128	3.76%	102.014	0.04%
1E+14	0.99	1,194,410,728	3.17%	109.283	0.03%
1E+06	0.85	1,195,769,607	3.06%	3.236	0.95%
1E+07	0.85	1,192,755,271	3.31%	3.771	0.88%
1E+08	0.85	1,195,716,218	3.07%	4.271	0.72%
1E+09	0.85	1,192,038,852	3.36%	4.876	0.69%
1E+10	0.85	1,097,429,443	11.03%	5.176	2.13%
1E+11	0.85	1,206,637,999	2.18%	5.755	0.38%
1E+12	0.85	1,216,504,201	1.38%	6.146	0.22%
1E+13	0.85	1,105,794,040	10.36%	6.714	1.54%
1E+14	0.85	1,217,616,092	1.29%	7.195	0.18%
1E+14	0.90	1,191,836,188	3.38%	11.042	0.31%
1E+13	0.90	1,188,694,863	3.63%	10.437	0.35%
1E+12	0.90	1,090,253,126	11.62%	9.266	1.25%
1E+11	0.90	1,214,256,201	1.56%	8.933	0.17%
1E+10	0.90	1,155,380,762	6.34%	8.409	0.75%

Initial T	α	Minimum Cost	Percent improvement	Time elapsed (min)	Percent improvement per minute
1E+09	0.90	1,175,281,923	4.72%	7.890	0.60%
1E+08	0.90	1,178,169,017	4.49%	7.059	0.64%
1E+07	0.90	1,193,222,374	3.27%	6.752	0.48%
1E+06	0.90	1,194,499,204	3.16%	5.749	0.55%
1E+06	0.95	1,189,772,870	3.55%	10.314	0.34%
1E+07	0.95	1,157,320,477	6.18%	11.722	0.53%
1E+08	0.95	1,139,684,254	7.61%	12.771	0.60%
1E+09	0.95	1,146,953,426	7.02%	14.259	0.49%
1E+10	0.95	1,144,987,470	7.18%	16.040	0.45%
1E+11	0.95	1,214,890,298	1.51%	17.639	0.09%
1E+12	0.95	1,233,529,944	0.00%	19.518	0.00%
1E+13	0.95	1,233,040,607	0.04%	20.396	0.00%
1E+14	0.95	1,196,962,336	2.96%	21.615	0.14%
1E+06	0.99	1,108,219,957	10.16%	48.304	0.21%
1E+07	0.99	1,128,084,569	8.55%	55.887	0.15%
1E+08	0.99	1,123,523,689	8.92%	65.030	0.14%
1E+09	0.99	1,218,965,393	1.18%	72.227	0.02%
1E+10	0.99	1,223,215,167	0.84%	81.136	0.01%
1E+11	0.99	1,145,942,306	7.10%	91.030	0.08%
1E+12	0.99	1,233,529,944	0.00%	95.466	0.00%
1E+13	0.99	1,178,317,407	4.48%	103.583	0.04%
1E+14	0.99	1,225,226,459	0.67%	111.156	0.01%
1E+06	0.85	1,196,653,363	2.99%	3.100	0.96%
1E+06	0.90	1,198,124,992	2.87%	4.709	0.61%
1E+06	0.95	1,095,341,576	11.20%	9.619	1.16%
1E+06	0.99	1,175,088,389	4.74%	49.335	0.10%
1E+07	0.85	1,174,070,864	4.82%	3.567	1.35%
1E+07	0.90	1,196,303,002	3.02%	5.456	0.55%
1E+07	0.95	1,193,898,641	3.21%	11.448	0.28%
1E+07	0.99	1,139,111,593	7.65%	59.101	0.13%
1E+08	0.85	1,181,113,846	4.25%	4.364	0.97%
1E+08	0.90	1,099,232,783	10.89%	6.415	1.70%
1E+08	0.95	1,159,983,609	5.96%	13.026	0.46%
1E+08	0.99	1,120,365,673	9.17%	66.621	0.14%
1E+09	0.85	1,197,471,747	2.92%	4.553	0.64%
1E+09	0.90	1,135,147,941	7.98%	7.018	1.14%
1E+09	0.95	1,110,562,965	9.97%	14.328	0.70%
1E+09	0.99	1,198,851,987	2.81%	73.058	0.04%
1E+10	0.85	1,140,473,630	7.54%	5.038	1.50%
1E+10	0.90	1,093,848,578	11.32%	7.859	1.44%
1E+10	0.95	1,141,315,058	7.48%	15.876	0.47%

Initial T	α	Minimum Cost	Percent improvement	Time elapsed (min)	Percent improvement per minute
1E+10	0.99	1,210,310,874	1.88%	80.723	0.02%
1E+11	0.85	1,159,795,111	5.98%	5.546	1.08%
1E+11	0.90	1,202,017,954	2.55%	8.549	0.30%
1E+11	0.95	1,224,584,817	0.73%	17.368	0.04%
1E+11	0.99	1,214,890,298	1.51%	88.123	0.02%
1E+12	0.85	1,200,722,333	2.66%	6.106	0.44%
1E+12	0.90	1,115,839,720	9.54%	9.187	1.04%
1E+12	0.95	1,113,895,640	9.70%	18.852	0.51%
1E+12	0.99	1,233,529,944	0.00%	95.964	0.00%
1E+13	0.85	1,186,656,291	3.80%	6.469	0.59%
1E+13	0.90	1,132,843,313	8.16%	10.026	0.81%
1E+13	0.95	1,211,423,525	1.79%	20.453	0.09%
1E+13	0.99	1,214,944,172	1.51%	103.559	0.01%
1E+14	0.85	1,228,368,326	0.42%	7.282	0.06%
1E+14	0.90	1,107,731,388	10.20%	10.739	0.95%
1E+14	0.95	1,214,890,298	1.51%	21.833	0.07%
1E+14	0.99	1,171,047,505	5.07%	111.603	0.05%
1E+06	0.85	1,179,870,994	4.35%	3.105	1.40%
1E+06	0.90	1,171,851,546	5.00%	4.663	1.07%
1E+06	0.95	1,191,849,874	3.38%	9.509	0.36%
1E+06	0.99	1,090,302,624	11.61%	49.605	0.23%
1E+07	0.85	1,194,586,085	3.16%	3.529	0.89%
1E+07	0.90	1,190,834,291	3.46%	5.405	0.64%
1E+07	0.95	1,139,188,336	7.65%	11.048	0.69%
1E+07	0.99	1,088,403,591	11.77%	56.025	0.21%
1E+08	0.85	1,204,607,964	2.34%	3.999	0.59%
1E+08	0.90	1,160,944,387	5.88%	6.164	0.95%
1E+08	0.95	1,182,674,274	4.12%	12.694	0.32%
1E+08	0.99	1,156,895,731	6.21%	63.896	0.10%
1E+09	0.85	1,169,728,005	5.17%	4.472	1.16%
1E+09	0.90	1,204,812,654	2.33%	6.891	0.34%
1E+09	0.95	1,182,217,121	4.16%	14.050	0.30%
1E+09	0.99	1,050,479,174	14.84%	71.509	0.21%
1E+10	0.85	1,102,578,690	10.62%	4.963	2.14%
1E+10	0.90	1,187,496,413	3.73%	7.878	0.47%
1E+10	0.95	1,210,292,877	1.88%	15.613	0.12%
1E+10	0.99	1,084,531,123	12.08%	79.298	0.15%
1E+11	0.85	1,137,694,723	7.77%	5.607	1.39%
1E+11	0.90	1,159,432,452	6.01%	8.310	0.72%
1E+11	0.95	1,189,365,594	3.58%	17.101	0.21%
1E+11	0.99	1,229,490,608	0.33%	86.918	0.00%

Initial T	α	Minimum Cost	Percent improvement	Time elapsed (min)	Percent improvement per minute
1E+12	0.85	1,214,279,174	1.56%	5.918	0.26%
1E+12	0.90	1,163,495,084	5.68%	9.090	0.62%
1E+12	0.95	1,144,751,782	7.20%	18.591	0.39%
1E+12	0.99	1,227,425,442	0.49%	94.544	0.01%
1E+13	0.85	1,150,869,269	6.70%	6.386	1.05%
1E+13	0.90	1,172,252,870	4.97%	9.833	0.51%
1E+13	0.95	1,194,274,723	3.18%	20.146	0.16%
1E+13	0.99	1,228,464,071	0.41%	102.362	0.00%
1E+14	0.85	1,132,907,078	8.16%	6.863	1.19%
1E+14	0.90	1,186,251,418	3.83%	10.540	0.36%
1E+14	0.95	1,193,104,109	3.28%	21.588	0.15%
1E+14	0.99	1,208,217,892	2.05%	110.499	0.02%
1E+06	0.85	1,198,552,466	2.84%	3.275	0.87%
1E+06	0.90	1,173,903,202	4.83%	4.683	1.03%
1E+06	0.95	1,140,450,414	7.55%	9.547	0.79%
1E+06	0.99	1,139,179,796	7.65%	48.388	0.16%
1E+07	0.85	1,196,653,363	2.99%	3.707	0.81%
1E+07	0.90	1,192,879,353	3.30%	5.422	0.61%
1E+07	0.95	1,191,812,626	3.38%	11.037	0.31%
1E+07	0.99	1,115,893,549	9.54%	56.223	0.17%
1E+08	0.85	1,182,624,336	4.13%	4.008	1.03%
1E+08	0.90	1,201,666,006	2.58%	6.163	0.42%
1E+08	0.95	1,142,622,242	7.37%	12.533	0.59%
1E+08	0.99	1,187,530,097	3.73%	63.839	0.06%
1E+09	0.85	1,136,118,232	7.90%	4.480	1.76%
1E+09	0.90	1,089,899,870	11.64%	6.917	1.68%
1E+09	0.95	1,129,285,508	8.45%	14.059	0.60%
1E+09	0.99	1,233,529,944	0.00%	71.532	0.00%
1E+10	0.85	1,150,394,837	6.74%	4.949	1.36%
1E+10	0.90	1,182,435,549	4.14%	7.649	0.54%
1E+10	0.95	1,219,706,849	1.12%	15.584	0.07%
1E+10	0.99	1,102,637,233	10.61%	79.378	0.13%
1E+11	0.85	1,147,252,663	6.99%	5.573	1.25%
1E+11	0.90	1,229,722,287	0.31%	8.378	0.04%
1E+11	0.95	1,174,249,529	4.81%	17.074	0.28%
1E+11	0.99	1,225,359,493	0.66%	87.170	0.01%
1E+12	0.85	1,189,017,702	3.61%	5.920	0.61%
1E+12	0.90	1,180,204,332	4.32%	9.111	0.47%
1E+12	0.95	1,210,550,181	1.86%	18.762	0.10%
1E+12	0.99	1,206,488,168	2.19%	94.839	0.02%
1E+13	0.85	1,140,471,948	7.54%	6.405	1.18%

Initial T	α	Minimum Cost	Percent improvement	Time elapsed (min)	Percent improvement per minute
1E+13	0.90	1,163,868,307	5.65%	9.817	0.58%
1E+13	0.95	1,204,357,658	2.36%	20.143	0.12%
1E+13	0.99	1,223,893,009	0.78%	102.477	0.01%
1E+14	0.85	1,129,373,936	8.44%	6.864	1.23%
1E+14	0.90	1,207,104,173	2.14%	10.689	0.20%
1E+14	0.95	1,232,630,806	0.07%	21.619	0.00%
1E+14	0.99	1,222,661,064	0.88%	110.087	0.01%
1E+06	0.85	1,198,479,229	2.84%	3.067	0.93%
1E+06	0.90	1,182,642,883	4.13%	4.661	0.89%
1E+06	0.95	1,188,607,863	3.64%	9.527	0.38%
1E+06	0.99	1,069,507,324	13.30%	48.489	0.27%
1E+07	0.85	1,200,486,785	2.68%	3.532	0.76%
1E+07	0.90	1,177,721,965	4.52%	5.471	0.83%
1E+07	0.95	1,185,527,236	3.89%	11.046	0.35%
1E+07	0.99	1,119,137,680	9.27%	56.156	0.17%
1E+08	0.85	1,200,259,384	2.70%	3.987	0.68%
1E+08	0.90	1,113,241,166	9.75%	6.142	1.59%
1E+08	0.95	1,109,959,018	10.02%	12.547	0.80%
1E+08	0.99	1,145,097,053	7.17%	66.059	0.11%
1E+09	0.85	1,197,499,946	2.92%	4.848	0.60%
1E+09	0.90	1,124,540,933	8.84%	7.282	1.21%
1E+09	0.95	1,173,414,719	4.87%	14.828	0.33%
1E+09	0.99	1,206,698,815	2.18%	76.631	0.03%
1E+10	0.85	1,213,402,721	1.63%	5.657	0.29%
1E+10	0.90	1,164,169,807	5.62%	8.421	0.67%
1E+10	0.95	1,156,243,933	6.27%	17.052	0.37%
1E+10	0.99	1,212,907,951	1.67%	89.426	0.02%
1E+11	0.85	1,233,529,944	0.00%	5.854	0.00%
1E+11	0.90	1,158,719,862	6.06%	8.859	0.68%
1E+11	0.95	1,179,549,682	4.38%	19.364	0.23%
1E+11	0.99	1,219,849,964	1.11%	99.218	0.01%
1E+12	0.85	1,197,704,046	2.90%	6.646	0.44%
1E+12	0.90	1,174,386,041	4.79%	10.192	0.47%
1E+12	0.95	1,219,625,151	1.13%	20.733	0.05%
1E+12	0.99	1,233,529,944	0.00%	104.001	0.00%
1E+13	0.85	1,179,640,416	4.37%	6.796	0.64%
1E+13	0.90	1,082,919,905	12.21%	10.416	1.17%
1E+13	0.95	1,109,081,536	10.09%	21.414	0.47%
1E+13	0.99	1,161,080,855	5.87%	109.138	0.05%
1E+14	0.85	1,179,725,395	4.36%	7.375	0.59%
1E+14	0.90	1,169,783,787	5.17%	11.329	0.46%

Initial T	α	Minimum Cost	Percent improvement	Time elapsed (min)	Percent improvement per minute
1E+14	0.95	1,143,953,729	7.26%	23.321	0.31%
1E+14	0.99	1,208,118,303	2.06%	118.074	0.02%
1E+06	0.85	1,192,797,789	3.30%	3.330	0.99%
1E+06	0.90	1,196,464,384	3.00%	5.057	0.59%
1E+06	0.95	1,142,686,213	7.36%	10.196	0.72%
1E+06	0.99	1,176,222,471	4.65%	52.407	0.09%
1E+07	0.85	1,189,324,282	3.58%	3.979	0.90%
1E+07	0.90	1,177,695,616	4.53%	5.818	0.78%
1E+07	0.95	1,185,527,236	3.89%	11.912	0.33%
1E+07	0.99	1,155,981,685	6.29%	60.254	0.10%
1E+08	0.85	1,196,389,744	3.01%	4.261	0.71%
1E+08	0.90	1,091,845,399	11.49%	6.652	1.73%
1E+08	0.95	1,092,501,435	11.43%	13.338	0.86%
1E+08	0.99	1,090,664,827	11.58%	67.909	0.17%
1E+09	0.85	1,168,049,717	5.31%	4.758	1.12%
1E+09	0.90	1,185,189,663	3.92%	7.310	0.54%
1E+09	0.95	1,172,234,219	4.97%	14.971	0.33%
1E+09	0.99	1,122,976,158	8.96%	75.881	0.12%
1E+10	0.85	1,163,628,036	5.67%	5.276	1.07%
1E+10	0.90	1,160,780,260	5.90%	8.305	0.71%
1E+10	0.95	1,225,940,978	0.62%	16.776	0.04%
1E+10	0.99	1,035,116,034	16.09%	84.165	0.19%
1E+11	0.85	1,139,793,671	7.60%	5.929	1.28%
1E+11	0.90	1,213,574,523	1.62%	8.865	0.18%
1E+11	0.95	1,124,865,370	8.81%	18.328	0.48%
1E+11	0.99	1,219,849,964	1.11%	92.484	0.01%
1E+12	0.85	1,233,529,944	0.00%	6.282	0.00%
1E+12	0.90	1,218,642,428	1.21%	9.657	0.12%
1E+12	0.95	1,076,245,079	12.75%	19.783	0.64%
1E+12	0.99	1,215,115,110	1.49%	100.787	0.01%
1E+13	0.85	1,168,926,729	5.24%	6.933	0.76%
1E+13	0.90	1,220,511,558	1.06%	10.405	0.10%
1E+13	0.95	1,177,540,771	4.54%	21.431	0.21%
1E+13	0.99	1,192,008,794	3.37%	108.867	0.03%
1E+14	0.85	1,129,983,845	8.39%	7.578	1.11%
1E+14	0.90	1,167,082,060	5.39%	11.328	0.48%
1E+14	0.95	1,197,467,955	2.92%	22.969	0.13%
1E+14	0.99	1,229,703,666	0.31%	117.114	0.00%

APPENDIX M.

SIMULATED ANNEALING CASE STUDY RESULTS

One of the results obtained during the sample testing for the ideal initial T and α was analyzed to see the costs compared to the base case (Table M.1).

Table M.1: Component and total costs from one simulated annealing output

		Maintenance direct cost	Maintenance delay cost	Acute disruption	Slow Orders	Routing cost	Total
Single track - short detour	Base	$6,595,266	$30,505,589	$181,187	$178,955,962	$2,618	$216,238,004
	Optimized	$8,212,150	$23,096,479	$221,011	$139,553,287	$3,350	$171,082,928
Single track - long detour	Base	$6,595,266	$30,505,589	$181,187	$178,955,962	$2,618	$216,238,004
	Optimized	$7,837,223	$34,102,697	$181,175	$149,333,421	$2,656	$191,454,516
Double track - short detour	Base	$13,190,533	$29,056,903	$362,374	$357,911,924	$2,618	$400,521,733
	Optimized	$13,196,711	$4,349,787	$287,416	$373,744,887	$2,571	$391,578,801
Double track - long detour	Base	$13,190,533	$29,056,903	$362,374	$357,911,924	$2,618	$400,521,733
	Optimized	$15,046,806	$29,538,464	$482,658	$315,022,024	$3,025	$360,089,952
Total	Base	$39,571,598	$119,124,983	$1,087,121	$1,073,735,772	$10,471	$1,233,519,474
	Optimized	$44,292,890	$91,087,427	$1,172,261	$977,653,618	$11,603	$1,114,206,196