Schedule Disruptions for Risk Comparisons in Engineering and Enterprise Systems

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Abstract

The systems engineer is challenged with building an understanding and collecting knowledge about the multiple dimensions, functions, and perspectives of systems and allocating resources to improve their design, operations, and other decision making processes. Risk analysis has a role of identifying, assessing and tracking emergent and future conditions that drive the dynamics of systems. However, the literature of comparative risk analysis in the 1990s to the present fell short of its aim that risk analysis could inform resource allocations across domains of health, environment, ecology, workplace safety, engineering, humans and organizations, finance, etc.—yet such span of domains is a distinguishing feature of complex systems. Among others, there was an objection that losses of lives, damages, finances, etc., should not be equated or balanced by multiplicative factors or other mathematical functions. Thus, there remains a gap to use risk analysis to quantify the degrees of concern (or the warranted levels of investment to allay those concerns) across non-comparable entities. Modeling and mathematical disruption theory offers a way that formerly non-comparable sources of risk can be compared, at least in part, by the degree of disruption to the schedules that constitute enterprises and problem domains. This dissertation will model systems in terms of their *schedules* of elements and, subsequently, quantify and compare the disruptions of the schedules by combinations of emergent and future conditions. The result is a characterization of the disruptions that most and least matter across formerly non-comparable domains. A framework and methodology will consist of (i) a literature review (ii) adopting a system analysis of schedules, (iii) composing disruptions as emergent and future conditions into operations disruptions, perspective disruptions, and time frame disruptions, (iv) testing of the schedules by each of the disruptions, (v) identifying the disruptions that most and least matter to the schedules, (vi) finding implications for information to collect on particular

emergent and future conditions in a process of monitoring. The approach supplements the traditional conceptions of risk as (a) probability and severity of adverse effects (Lowrance, 1976), (b) effect of uncertainty on objectives (International Organization for Standardization, 2009), (c) influence of scenarios to priorities (Lambert et al. 2009-2017), etc.), and extends risk analysis to address "the impact of disruption of schedules". The developed theory and methodology are demonstrated with application to scheduling at a marine container port with disruptions of operations, perspectives, and time frames.

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List of abbreviations

IDEF	Integrated Definition Methods
INCOSE	International Council on Systems Engineering
KL-divergence	Kullback-Leibler divergence
NIT	Norfolk International Terminals
NNMT	Newport News Marine Terminal
PMT	Portsmouth Marine Terminal
RFID	Radio-Frequency Identification
RMT	Richmond Marine Terminal
SRA	Society for Risk Analysis
TEU	Twenty-Foot Equivalent Unit
VIG	Virginia International Gateway
VIP	Virginia Inland Port

Chapter 1

Introduction

Overview

This section introduces the content of the dissertation, its purpose and scope. The motivation for the research is discussed, the research questions and problems are stated. The purpose and scope for later chapters are discussed along with expected contributions. The chapter concludes with definitions of key terms and an illustration of the organization of the remainder of the dissertation.

Motivation

In systems analysis and engineering, a *schedule* (or *scheduling)* is an ordered list of system elements, typically with associated time, location, cost, and other constraints (Conway et al. 2003; Pinedo, 2016). Owner/operators of engineering and enterprise systems collect ever-increasing amounts of data to adjust *schedules* of their assets, projects, organizational units, investments, policies, environments, etc. The value of the data depends in part on the ability of system owner/operators to leverage it in *scheduling* to understand and increase their business wealth and productivity. Methods and techniques for big data analytics of schedules have thus proliferated among practitioners of systems engineering. It can be useful to link the outcomes of analytics to schedule impacts such that the return on investment in analytic capabilities can be assessed (Deloitte, 2017). For logistics schedules in particular, organizations are beginning to widen the scope of their procedural design, and take a more holistic approach to network design and optimization (Loh et al., 2016). The systems engineer (INCOSE, n.d.) has an important role in providing research, methods and tools to aid in the development of metrics, models, solutions, methods for both *schedules* and the potential *disruptions* to those schedules. Furthermore, risk analysis has key roles including to identify and track the emergent and future conditions to which the schedules might be exposed, and understanding the impacts of these conditions (Thorisson et al. 2017; Karvetski et al. 2009).

Examples of systems with multiple, sometimes competing objectives are ubiquitous. In the 1960s, Feldbaum (1960) introduced the concept of dual control. When controlling a system, at least two objectives must be considered: (i) driving the system towards its desired state and (ii) actively learn and gather information to reduce uncertainty about system parameters. The theory was challenging for practical implications although many approximations and numerical solutions were developed (Wittenmark, 1995). In the era of big data, the principles of dual control have increasing importance and modern applications have been identified in economic systems, manufacturing, information retrieval, robotics, and other domains (Fu, 2017). Conceptually, the tradeoff in dual control is similar to the exploitation-exploration tradeoff that lies at the core of many modern machine learning techniques. Bayesian reinforcement learning (Ghavamzadeh et al. 2015; Klenske & Hennig, 2016) deals with balancing the objective of maximizing some reward with learning about the system which could later be used to gain an even higher reward and ensuring the algorithm does not converge onto a local, but not global, maximum. In the context of risk analysis, scenarios are frequently used to explore and learn about the emergent and future conditions a system can be exposed to. Objectives include minimizing the expected or maximum loss or achieving a level of performance with an acceptable level of risk. Thus, risk analysis and risk management are tasked with the same tradeoff dilemma.

Purpose and scope

Enterprises have strategic and tactical priorities and values that evolve over time. The priorities are manifested in the various schedules of the enterprises: investments, operations, workforce development, and others. Disruptions of various kinds can trigger a re-evaluation of those priorities and thus an update of schedules.

The purpose of this effort is to identify and quantify *disruptions* to *schedules* of complex systems. Studying the disruption of schedules extends the comparison of risks across a variety of problem domains such as health, environment, communication, economics, etc. beyond the comparison of likelihood and consequences. The approach includes (i) to create and evaluate schedules that are subject to a variety of disruptions, (ii) to develop metrics to quantify the disruption of schedules when stressed by internal and external emergent and future conditions, and (iii) to contribute to a general theory of how schedule disruptions are propagated in complex systems of interest to systems engineers.

Similarity metrics from statistics, ecology, information science, and machine learning enable the comparison of sets of outcomes or probability distributions (Choi & Lee, 2003; Condit et al. 2006; Leydesdorff, 2008). Re-purposing and adapting these metrics to engineering application provides metrics for schedule disruption. Building on a definition of risk as "the effect of uncertainty to objectives" (International Organization for Standardization (ISO) 2009), the theory and methods developed will show how disruptions can change the trade-offs between different system objectives. An instance of this is the re-prioritization of system elements under the influence of combinations of emergent and future conditions. Previously, scenario-based preferences (Lambert et al. 2013; Connelly et al. 2015; Karvetski and Lambert 2012) quantified risk as the *influences of scenarios to priorities*. Elements of strategic plans were prioritized and reprioritized under various scenarios of socio-economic, environmental, policy, security factors, among others. However, analysis of risk via scenario-based preferences has been limited to ordinal rankings. In part, this dissertation will extend the theory to schedules where the order can have additional constraints of time, location, cost, etc. with some probabilistic elements. Thus it advances risk analysis by studying the *influences of disruptions to enterprise schedules*.

Contributions

The dissertation makes contributions to the theory, methods, and applications of systems engineering. These are summarized below and discussed in detail in Chapter 10. The italicized terms are defined in the "Key terms" section later in Chapter 1.

- Contribution 1: Modeling framework for *scheduling* with stochastic model elements. Formulation of a mixed-integer linear model and Monte Carlo simulation assigning ships to locations and times given a set of requirements.
- Contribution 2: Quantification of schedule *disruptions* for risk comparisons across domains. Development of measures that quantify disruptions of both *schedule assignments* and *schedule performance*. The measures have a theoretical foundation in probability, set theory, information theory, and others.
- Contribution 3: *Model-informed* operational disruption analysis. Applying the modeling framework to evaluate impacts of operational disruptions to scheduling.

- Contribution 4: Model-informed tradeoff analysis of schedules. Leveraging modeling framework to balance the multiple objectives of stakeholders, including schedule *operational costs, delays, and robustness*.
- Contribution 5: Model-informed *schedule option* development. Enumeration, filtering, and evaluation of deterministic schedule options based on the outputs of the modeling framework.
- Contribution 6: Demonstration of modeling framework for a marine container port system. The framework is implemented for the berthing of container vessels at the Port of Virginia, USA.

Key terms

This section defined key terms in the dissertation. Although not a comprehensive list of all technical terms pertaining to the theory, methods, and applications, it summarizes those with the most relevance to the innovations and contributions.

Theory/methods

Schedule/Scheduling: In this dissertation, a *schedule* refers to a list of system elements, each with associated time and location assignments and some measures of performance. The definition allows time, location, and other factors of the schedule elements to be deterministic or probabilistic, represented by random variables. *Scheduling* is a process of creating, updating, and adjusting schedules.

Emergent and future conditions: *Emergent and future conditions* are uncertain factors that can influence outcome, performance, or decision making of a system. The can be internal to the system, such as policies or projections advocated by a group of stakeholders, or external, such as natural disasters, macroeconomic shifts, and others (Thorisson et al. 2017).

Schedule disruption: A *disruption* is a combination of emergent and future conditions that has potential to cause deviations of schedules, both assignments and performance. In this dissertation, measures are proposed for the quantification of schedule disruptions.

Schedule option: A *schedule option* is a deterministic instance of a schedule. In other words, if a schedule representation includes random variables a schedule option is an operationally feasible realization of the random variables.

Schedule assignment: The prioritization of time, location, and other resources allocated to schedule elements is referred to as *schedule assignment*. For instance, schedule assignment includes deciding which terminal a container ship berth at and what time it is berthed.

Schedule performance: The costs, delays, resource utilizations, and other indicators resulting from a schedule assignment are collectively referred to as *schedule performance*.

Risk analysis: In line with the glossary of the Society for Risk Analysis, the study of *risk analysis* in the context of this dissertation includes "*risk assessment, risk characterization, risk communication, risk management, and policy relating to risk, in the context of risks of concern to individuals, to public and private sector organizations, and to society at a local, regional, national, or global level* (Aven et al., 2018)."

Model-informed: A model-informed approach, a term from the biomedical community, "*aims to integrate information from diverse data sources to help decrease uncertainty […], and to develop information that cannot or would not be generated experimentally* (Cukier-Meisner, 2017)."

Demonstration

Port: In this dissertation, a *port* is the physical infrastructure and the organization governing intermodal transactions of goods, in particular loading and unloading ships and providing transfer to trucks, trains, and other modes of transportation carrying goods.

Terminal: A *terminal* is a specific location within a port providing infrastructure to load and unload ships and transfer to trucks, trains, and other modes of transportation.

Berth: A *berth* is a section along the quay of a terminal where a ship "parks" while goods are loaded and unloaded.

Vessel: A *vessel* in the context of this dissertation is a container ship transporting containerized goods between marine ports. Used interchangeably with ship.

Operational cost: The expenses incurred by the port when loading and unloading a vessel. These include labor, equipment operations and maintenance, and others but exclude capital cost and other overhead expenses shared across the port organization.

Delay: The time that passes between the arrival of a vessel at the port until it is berthed at a terminal.

Schedule robustness: The stability of schedules to variations in input variables is referred to as schedule robustness (Goren & Sabuncuoglu, 2009; Wang & Meng, 2012). Most specifically, in this dissertation a robust schedule has high certainty about assignment of resources in the face of variations.

Organization of dissertation

This dissertation is organized into several chapters. Chapter 1 provided a motivation for the topics of the dissertation, described the purpose and scope, and the organization of the remainder of the dissertation.

Chapter 2 provides a survey of literature on the relevant theory, methods, and applications of system scheduling and disruptions in logistics, infrastructure, and other fields.

Chapter 3 describes the methodological framework developed. The framework includes a technical approach to modeling schedules, elicit disruptions of operations, perspectives, and different time frames, and quantification of the disruptions to the modeled schedules.

Chapter 4-8 demonstrate the framework through case studies in scheduling at maritime container ports. Specifically, Chapter 4 introduces the domain of the container port schedules and a system analysis identifies the major stakeholders, uncertainties, and time frames associated with the various scheduling activities, particularly vessel berth scheduling. Chapter 5 studies disruptions to vessel berth scheduling from emergent and future conditions that affect the operations capacity of the port. Chapter 6 quantifies how multiple, possibly conflicting, perspectives can disrupt the vessel berth scheduling. Chapter 7 considers a different time frame and analyzes how scheduling is disrupted when the planning horizon changes. Chapter 8 studies scheduling of truck operations and compares and contrasts operations based on a key performance indicator.

Chapter 9 provides a discussion of the topics of the dissertation, including theoretical and methodological challenges and limitations, model testing and evaluation, and extensions to other domains.

Chapter 10 summarizes the significance and contributions of the dissertation to literature and practice, and identifies areas of future work.

Figure 1-1 illustrates the organization of dissertation.

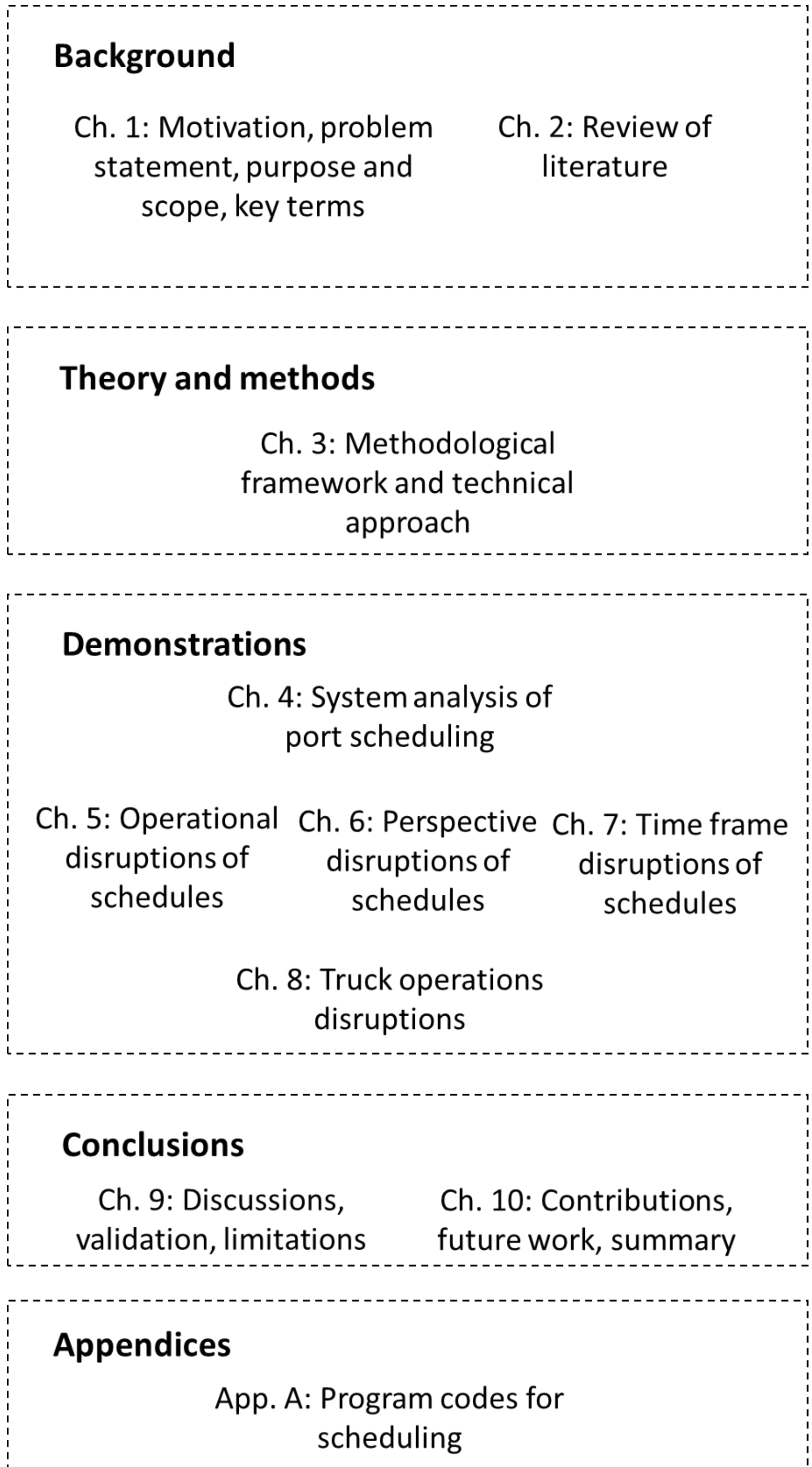

Figure 1-1. Organization and roadmap of dissertation.

Chapter 2

Literature review

Overview

This chapter will give an overview of relevant literature on schedule disruptions. It is organized into three parts: (i) theory, (ii) methods, and (iii) applications. Table 2-1 summarizes the contents of the chapter.

Table 2-1. Overview of Chapter 2, where literature is identified and discussed.

Chapter objective	Identification of the literature of scheduling and schedule disruptions
Motivation	Establishing the theoretical, methodological, and practical foundation for the remainder of the dissertation
Approach and data	Review of journals of systems engineering, risk analysis, operations research, probability and statistics, logistics, and others
Contributions	Comprehensive overview of definitions of schedule disruptions and measures of quantification, including Jaccard index, overlap coefficient, Bhattacharyya distance, and others

Theory

Systems engineering provides a framework for problem domains that are characterized by increasing complexity, uncertainty, emergent properties, and ambiguity about system boundaries (Jaradat et al. 2017). Systems analysis (Gibson et al. 2016) with its associated theory, methodology and tools addresses value creation in engineering and enterprise systems. Hierarchical holographic modeling (Haimes 2016, 1981) offers a way to decompose large-scale systems into smaller individual systems (hierarchy) from multiple viewpoints or perspectives (holographic). Brugnach et al. (2008) address the multifarious nature of decision problems in terms of uncertainty. They consider ambiguity, or multiple knowledge frames, as a type of uncertainty along with epistemic and aleatory. Scenario planning has been useful in exploring uncertainties of complex systems where probabilities are derived from expert opinions and subject to cognitive bias (Goodwin & Wright, 2001). This is particularly relevant to developing situations facing inherent deep uncertainties (Karvetski et al., 2009; Boin and McConnell 2007). In contrast to risk analysis that focuses on probabilities and consequences, resilience analysis *with scenario-based preferences*, has focused on quantifying the *influence of scenarios to priorities* (Almutairi et al. 2018; Karvetski et al. 2011; Quenum et al. 2019).

Theoretical definitions of *scheduling* share concepts such as order, time, allocation of resources, and others. Conway et al (2003) define scheduling as the process of constructing an order of operations. Pinedo (2016) includes more specifics and defines scheduling by the "allocation of resources to tasks over given time periods and its goal is to optimize one or more objectives". The study of *disruptions* of schedules has caught the attention of researcher in recent years. Various definitions have been proposed but most share the notion that a *disruption* causes a deviation (from a baseline) in the performance of the schedules, in terms of time, cost, resource utilization, or other factors. Hassannayebi et al. (2016) define disruption as the occurrence of a disorder or deviation from initial plan and develop an approach to manage disruption in rail transit systems. In the context of critical infrastructure, disruption has been defined as the interruption to customer service demands (Thacker et al. 2017). The authors use network theory to build a system-of-systems model of infrastructure sectors and analyze how disruptions cascade through multiple scales and interconnected systems. In supply chains, Hishamuddin et al. (2013) define a *supply chain disruption* as an event that disrupts the material flow in the supply chain. They note that these events can be triggered by both internal and external factors. A similar dichotomy is noted by Katragjini et al. (2013), where manufacturing flow shop disruptions are classified as *capacity disruptions*, which relate to failure of machines or other internal sources, or *order disruptions*, that are caused by job cancellations, raw material shortages, and other external factors.

Li et al. (2016) further distinguish between *disruption events* and *regular uncertainties* in logistics. Regular uncertainties refer to relatively frequent occurrences that can be described with probability distributions derived from historical data. Examples of these uncertainties include travel times of trucks between two cities, downtimes of certain machines, and the number of containers on a vessel to be handled at a particular port. Regular uncertainties are often considered when schedules are created, such as when airlines add buffer times to published schedules. Disruption events on the other hand are less frequent or one-time events that are usually not considered in the scheduling process but can have significant effect on the schedule if they occur. Examples include weather events such as hurricanes, labor strikes, or indirect effects such as an accident closing a major highway diverts high volumes of traffic onto other roads.

Quantifying the disruptiveness of various scenarios to a schedule or plan is addressed by in scenario-based preferences by comparing prioritizations or timelines and using statistical measures such as Spearman rank correlation (Thorisson et al., 2017) or Kendall Tau-b coefficient (You et al. 2014). The disruptiveness measure is aimed at highlighting which scenarios (combinations of emergent and future conditions) most disrupt the schedule. To generalize the idea, a disruption function can be defined as a mapping from two schedules, Z, to a one or more (total of n) disruption measures:

$$d: Z_1 \times Z_2 \rightarrow \mathbb{R}^n \tag{1-1}$$

The disruption measures are based on the outputs of the schedule and thus there can be a disruption in cost, time, location, need for resources, and many others.

Of course, schedule disruption needs to be understood in a context of *uncertainty analysis*. Uncertainty in mathematical modeling has been classified into *epistemic* (knowledge, fundamental) and *aleatory* (variability, randomness) (Apostolakis, 1999; Kiureghian & Ditlevsen, 2007; Paté-Cornell, 1996). This bifurcation of uncertainty can assist identifying factors or areas where uncertainty can be reduced (epistemic) and where uncertainty is intrinsic to the problem (aleatory).

Walker et al. (2003) recognize that there are further dimensions of uncertainty beyond classifying it as reducible or irreducible. They identify three dimensions:

- Location of uncertainty: where in the model the uncertainty manifests itself. This includes uncertainty about context, model form, inputs, and parameters.

- Level of uncertainty: where on the spectrum between perfect knowledge to completely unknown the uncertainty falls. The authors specify four levels: statistical uncertainty, scenario uncertainty, recognized ignorance, and total ignorance.
- Nature of uncertainty: whether uncertainty is due to lack in knowledge (epistemic) or inherent variability of phenomena (aleatory).

Methods

Approaches for managing schedule disruption are generally either reactive, by optimizing recovery and adjusting schedules at the time of disruption occurrence, or proactive, which includes building robust and resilient schedules. Brouer et al. (2013) analyze recovery strategies of disruptions of liner shipping schedules by speeding up travel, swapping port calls, or omitting a port call. They note the tradeoff between speeding up, which increases fuel cost and emissions of CO_2 and other pollutants. Li et al. (2015) address the same problem but identify a threshold of delays where speeding up is no longer a feasible recovery option and swapping or omitting is recommended. In urban rail transit, Hua and Ong (2017) analyze the recovery duration and number pf passengers transferred to other modes during a disruption of rail services. Balancing the cost of switching from rail to bus with carbon emissions is considered by Fang and Jiang (2018). In aviation, Hu et al. (2015) develop an optimization method for reassigning passengers and aircraft following a significant delay or cancellation of a flight. Katragjini et al. (2013) develop an algorithm for rescheduling a manufacturing operation when facing multiple types of disruptions simultaneously.

The approaches reviewed in the previous paragraph assume the response to a disruption starts when it is close in time and there is a non-negligent probability that it will occur. Scenario analysis (Godet, 2000) can be useful to explore disruptions without an estimation of probabilities. Collier and Lambert (2018) schedule hurricane response activities and evaluate how disruptions of both project activities and shifting preferences of decision makers affect the execution of the schedule. Taleizadeh (2017) create manufacturing schedules that are robust to disruptions by planning for back-ordering.

Disruption measures are available for the above purposes in the literature of statistics and set theory. Three are reviewed here and mathematically defined in Table 2-1. The *overlap coefficient* is defined as the ratio of the intersection of two sets (or probability distributions) by the smaller of sets (minimum of the distributions) (Larson, 2014). Examples of use are comparing income distributions in economic analysis (Inman & Bradley Jr, 1989) and population migration (Clemons & Bradley, 2000). The *Jaccard index* is defined as the size of the intersection of two sets divided by the size of the union. The index is used in a variety of fields, such as measuring eco-diversity (Condit et al., 2006), default risk analysis of enterprises by analyzing interdependencies (Calabrese et al. 2017), and author co-citation analysis (Leydesdorff, 2008). Both the overlap coefficient and the Jaccard index can be formulated for either sets or probability distributions. A measure that is fully founded in probability is *Bhattacharyya distance*, defined as the integral of the square root of the product of two density functions. The measure is used in feature selection (Choi and Lee 2003; Guorong et al. 1996) and can be used to measure an upper bound on the probability of misclassification in a two class problem (Aherne et al. 1998).

Table 2-2. Overview of various disruption measures found in the academic literature of computer science, economics, ecology, and other fields.

Disruption measure	Definition	Source
Overlap coefficient (set formulation)	$OVL_{set} = \frac{\lvert X \cap Y \rvert}{\min(\lvert X \rvert, \lvert Y \rvert)}$	Larson, 2014 Inman & Bradley Jr, 1989
Overlap coefficient (probability formulation)	$OVL_{prob} = \int_{-\infty}^{\infty} \min\left(f_1(t), f_2(t)\right) dt$	Clemons & Bradley, 2000
Jaccard index (set formulation)	$J_{set} = \frac{\lvert X \cap Y \rvert}{\lvert X \cup Y \rvert}$	Calabrese et al. 2017 Leydesdorff, 2008
Jaccard index (probability formulation)	$J_{prob} = \frac{\int_{-\infty}^{\infty} \min\left(f_1(t), f_2(t)\right) dt}{\int_{-\infty}^{\infty} \max\left(f_1(t), f_2(t)\right) dt}$	Condit et al. 2006
Bhattacharyya distance	$BC = \int_{-\infty}^{\infty} \sqrt{f_1(t) f_2(t)} dt$	Choi and Lee 2003 Guorong et al. 1996 Aherne et al. 1996

Applications

As an example of scheduling in engineering, vessel scheduling at ports is a topic which has been studied in the operations research literature due to its mathematical structure (Alvarez et al. 2010; Robenek et al. 2012). The aim of the "berth allocation problem" is to find a combination of berthing times and locations at a quay that optimizes an objective function. Stahlbock and Voss (2008) and Bierwirth and Meisel (2015) give extensive overview of operations research methods used and classify different problem structures. Dulebenets et al. (2015) consider the case where vessels can be directed to a second terminal when there is excessive demand at designated locations. Uncertainty in vessel berthing problems (Budipriyanto et al. 2015) has been addressed by Monte-Carlo simulation (Dragovic et al. 2006; Alattar and Karkare 2006) and sensitivity analysis of parameters (Xu et al. 2012).

Scenario analysis has been used in freight transportation planning where rapid changes in the industry make historical data useless to decision making (Di Francesco et al. 2009). In other cases, such as when preparing for unprecedented large-scale high consequence but low probability events, different policies and responses can be explored using scenarios (Parlak et al. 2012; Lambert et al. 2013).

There are various other cases in the scientific literature where elements of a plan need to be arranged, or *scheduled,* in two or more dimensions, such as time and space. Scheduling construction activities has been researched in detail (Akinci et al. 2002; Thabet and Beliveau 1994) and risk analysis of construction workspace planning by identifying time-space conflicts has been proposed (Akinci et al. 2002). In environmental sciences, policies of restoration and conservation of eco-systems and natural environments have been prioritized in time and space by selecting appropriate locations at appropriate times given funding availability (Wilson et al. 2009; 2011; Rappaport et al. 2015).

Summary

Jaradat et al. (2017) identify in a recent paper seven attributes that characterize current research on complex systems. Table 2-2 lists the attributes and the extent to which this dissertation covers each one. The literature, in theory, applications, and methods, thus suggests a gap or opportunity for systems risk analysis by disruption of schedules as well as available theory and methodology on which to build.

Table 2-3. Attributes characterizing complex systems (Jaradat et al., 2017).

Attribute	Coverage by dissertation	Contribution
Increasing complexity	Significant	Method to quantify disruptions of multiple emergent and future conditions and perspectives
Ambiguity	Marginal	Incorporation of multiple perspective to counter ambiguity about system boundaries and objectives
High levels of uncertainty	Marginal	Description for various levels of uncertainty: historical fluctuations, uncertainty of emergent and future conditions, recognized uncertainty (e.g. data quality)
Emergence	Marginal	Anticipation of emergent behaviors
Evolutionary development	Significant	Identification of emergent and future conditions that might cause changes in the system and prioritization among disruptions of such conditions
Interconnectivity	Marginal	Utilizing methods that support modeling of interconnectivity among system elements
Integration	None	-

Chapter 3

Methodological framework

Overview

This section describes a methodological framework for modeling schedules and various disruptions of the schedules. First, a scheduling approach based on the generalized assignment model is modified to include stochastic inputs is formulated. Second, three types of disruptions, operations disruptions, perspective disruptions, and time frame disruptions, are described and techniques to model each type. Third is a formulation of measures, comparable across the three types, to quantify the degree of disruption. Fourth is a description of recommendations for data collection based on the findings in previous steps of the analysis. An overview of the chapter is provided in Table 3-1. Figure 3-1 describes technical elements of the approach. This includes defining model inputs, optimization and simulation requirements, and implications for disruptions and schedule option development.

Table 3-1. Overview of Chapter 3, describing the methodology and technical approach for scheduling and disruptions for risk comparisons.

Chapter objective	Delineation of framework of scheduling and modeling of various types of disruptions to the schedules
Motivation	Outlining the approach that is implemented and exercised in the dissertation
Approach and data	Formulation of generalized assignment model for scheduling including random input variables
	Identify adjustments of modeling approach for various types of disruptions
	Definition of disruption coefficient based in set theory and probability
Contributions	Formal incorporation of random input variables to assignment model for scheduling
	Derivation of disruption coefficient and interpretation for risk analysis

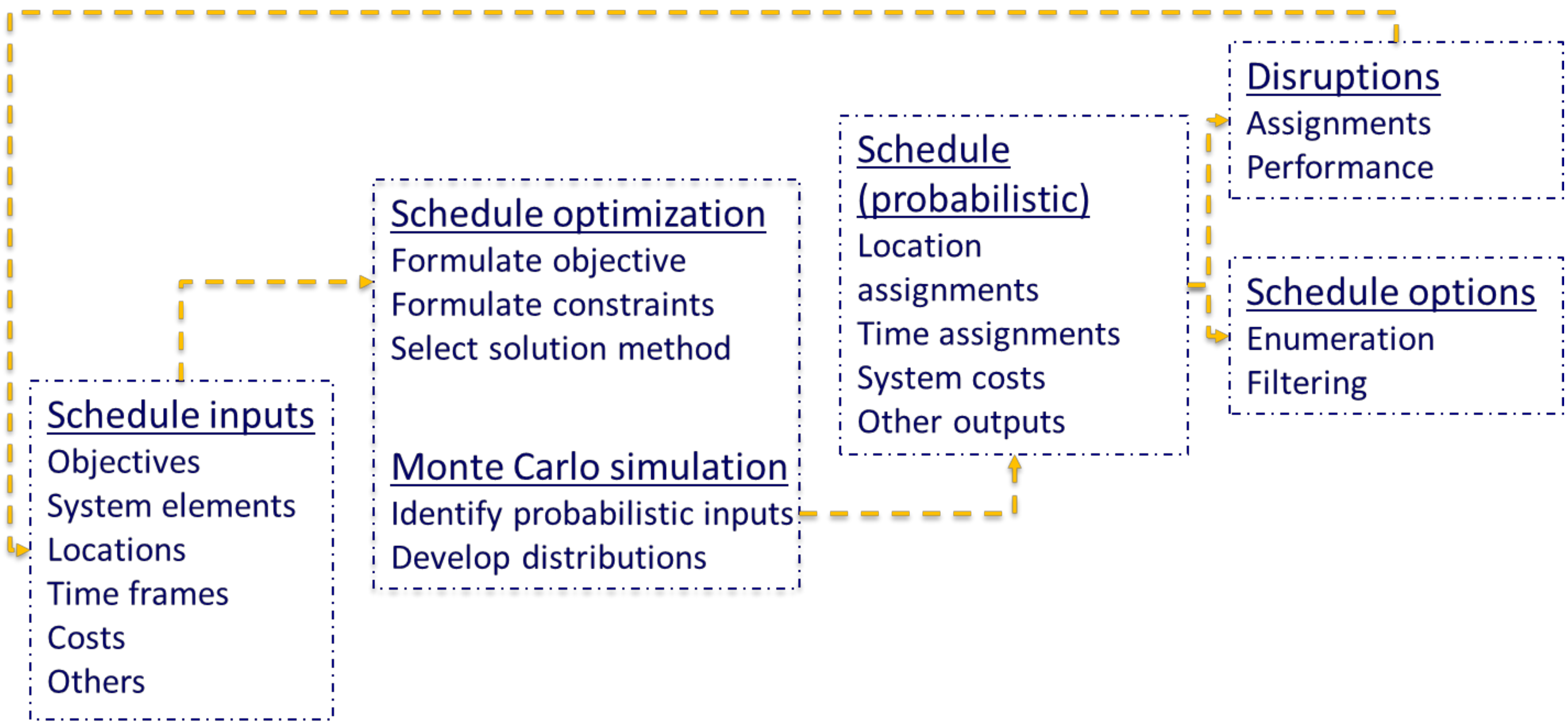

Figure 3-1. Flowchart describing elements of technical approach for modeling schedules, schedule disruptions, and quantifying the disruptions and schedule options.

Schedules

This section outlines schedule modeling as a component of system analysis. A first step in any systems analysis is to define the problem: What is the purpose of the analysis and in what context are the results interpreted. This includes identifying stakeholders and decision makers, resources they have and the time frames associated with the various stakes they hold and decisions they make. This describes what resources, time frames, and decisions are shared among stakeholders and what is independent. A goal is to set the scope of the schedules and create a context in which subsequent tasks in evaluated. Thus the analyst can at any moment go back and assess whether the boundaries of the analysis are consistent with the scope.

The approach is a review and development of models for scheduling. The models needs to be sufficiently detailed to provide a useful description of the phenomenon being modeled but general enough to be applicable to a variety of infrastructure systems and decision contexts. Scheduling, as any decision process, involves multiple stakeholders with different, sometimes conflicting, objectives. Thus, several scheduling strategies or perspectives should be formulated and evaluated, each representing a particular stakeholder objective.

The results from this step provide baseline schedules, assuming business-as-usual conditions. In subsequent tasks, disruptions to this baseline are introduced.

The generalized assignment problem

Various problems in systems engineering involve the assignment of some limited resources to meet a demand. This includes instances of scheduling, for example scheduling aircraft and crew for airline operations, scheduling manufacturing jobs to machines in factories, allocating computing resources to network users, as well as assigning container vessels to terminals at a marine port. A well-studied model in applied mathematics, known as the *general assignment problem* (Kundakcioglu & Alizamir, 2008), can serve as a starting point for the analysis of these problems. In its simplest form it is composed of assigning *n system elements (jobs)* to *m locations (agents)* while meeting an objective of minimizing cost (or maximizing profit). Assigning an element to a location requires use of some of the capacity of the location, which is limited. It is required that each element is assigned to exactly one location and that the capacity of each location is not exceeded. In mathematical terms, the problem can be written as

$$\min_{x} \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} x_{ij}$$

$$\text{Subject to} \quad \begin{array}{cc} \sum_{i=1}^{n} a_{ij} x_{ij} \leq b_j & \forall j \\ \sum_{j=1}^{m} x_{ij} = 1 & \forall i \\ x_{ij} \in \{0,1\} & \forall (i,j) \\ others & \end{array} \tag{3-1}$$

Here, x_{ij} are the decision variables with $x_{ij} = 1$ when system element i is assigned to location j and $x_{ij} = 0$ otherwise. The resources used when assigning element i is assigned to location j is a_{ij} and the cost is c_{ij}. The capacity of location j is b_j. The objective is to minimize the total cost of assignments. The first constraint ensures that the capacity of each location is not exceeded. The second constraint ensures that each element is assigned to exactly one location. This both serves the requirement that each element is assigned to a location as well as prohibiting that an element can be split up between two locations. The third constraint states that the decision variable is binary, i.e. there is no such thing as a partial assignment. In addition, there can be other constraints that are specific to each application. This can include setup times in machine scheduling, minimum rest time for airline crews, etc. In the demonstration, several constraints beyond the first three will be introduced.

A special case of the generalized assignment model is the *berth allocation problem* which is frequently used to model the scheduling of vessels at ports (Bierwirth & Meisel, 2015). The formulation of the model assigns a time and berthing location to each vessel considered for a given time period, while meeting an objective such as minimizing cost or delays. In this case it is assumed that inputs such as arrival time, container volume, and handling time are fixed and known. Recorded outputs, in addition to the time and location, are e.g. costs, deviations between arrival time and berth time, and facility utilization. The optimization problem is described in full detail in Chapter 4.

Addressing input uncertainty in generalized assignment problem

The majority of research on the generalized assignment problem, and operations research in general, finds a single solution that maximizes or minimizes the defined objective. In the most straightforward cases, all inputs (here, the values of a_{ij}, b_j, c_{ij}) are considered deterministic and known at the time of decision-making and the solution is a vector of deterministic decision variables x_{ij}. However, for many applications, the inputs are not deterministic but are described by probability distributions. For example, in vessel terminal assignment, there are week-to-week fluctuations in how many containers are carried by vessels which corresponds to a_{ij} when terminals have weekly capacity b_j.

Now, the generalized assignment problems is examined in the context of probabilistic inputs. The inputs are now random variables (A_{ij}, B_j, C_{ij}) that can follow any distribution. The decision variables, mapped from the probabilistic inputs, are no longer a binary vector of x_{ij}, rather each decision is represented by a Bernoulli random variable X_{ij} with parameter p_{ij}, $\{\forall p_{ij}: p_{ij} \in [0,1]\}$.

In addition to input and decision variables being represented by random variables, performance measures such as the system cost, $C = \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} x_{ij}$, follow a distribution.

In application, the input distributions can in many cases be fitted from historical data. Monte-Carlo simulation can then be used to derive the distributions for the decision variables and system cost. In Monte-Carlo simulation, a large number of iterations is run. In each run, a random sample of the input variables is used to populate the deterministic generalized assignment model and the decision variables and system cost is recorded. After all iterations have been completed, the distributions for the decision variables and system cost are derived.

In vessel berth scheduling, some input variables that are modeled as random variables with distributions fitted from historical data are arrival times of vessels, handling times, and container volume (the number of containers on each vessel). Drawing randomly from the input distributions, output distributions for the system cost, delays, utilizations, and vessel berthing times and locations are derived.

Disruptions

A *disruption* of a schedule is a combination of one or more emergent and future conditions with the potential to cause a deviation from a baseline in the performance of the schedules, in terms of time, cost, resource utilization, or other factors. Often times, there are reasons to anticipate that emergent and future conditions will be different from the past. *Emergent* refers to conditions that are realized by a more complete understanding of the system, revelation of new information, or reinterpretation of purpose and objectives. *Future* refers to future events or changes of mind. The conditions can be external, such as weather and flood events, or surges in demand for services before holidays, or internal, such as updates business objectives and procedures, or planned construction and maintenance. After compiling a list of emergent and future conditions, a disruption is defined by combining one or more of the conditions. Thus a disruption can be composed of an extreme weather event during a period of capacity limitation for maintenance.

The sources of disruptions, the emergent and future conditions, are diverse and are placed in three categories: operations disruptions, perspectives disruptions, and time frames disruptions. The three categories and different technical approaches of modeling them are explored in further detail in this section.

Operations disruptions

Operations disruptions refers to conditions where performance of schedules is affected but without triggering a re-evaluation of objectives and schedules processes. The impacts of the disruptions are tested by changing input variables to represent the conditions covered by the scenario. In the notation of the generalized assignment problem, this equates making changes to the parameter a_{ij} and b_j. A main difference between probabilistic scheduling, achieved using Monte-Carlo simulation, and the operations disruptions analysis is that the manipulation of inputs in the latter case is not dependent on historical data and can therefore include values previously not encountered but external trends or anticipations of stakeholders suggest that might be realized. This includes addition or closure of locations, changes in costs, the addition or removal of system elements, and others.

Perspectives disruptions

Systems have multiple stakeholders, each with their own set of goals and objectives which overlap to varying extents. The stakeholders have different levels of interest and power in influencing scheduling processes, and this balance can change over time. Perspective disruptions refers to the degree which different objectives affect performance of schedules, measured in cost, delays, and resource utilization. Modeling perspectives disruptions in the generalized assignment model is achieved by changing the objective function to represent the different perspectives, c_{ij} in the notation.

Time frames disruptions

Time frames play a central role in scheduling, as well as decision making in general (Haimes, 2012). Schedules are made for days, weeks, months, or years, often with a recurring cycle. Different time frames call for significantly different modeling approaches. For instance, scheduling in real time arrivals of trains to platforms can utilize a first-come first-serve policy while scheduling the train arrivals for a daily service lasting months or years requires more sophisticated approaches. The generalized assignment model with probabilistic elements, as described earlier, has a time frame associated with the input variables. In practice, such as in the train example, such a time frame could be repeated for a period much longer. In some cases it can be possible to update the schedule every time frame, taking into account the most recent information available and effectively reducing the uncertainty around a_{ij}, b_j, and other parameters in the model. However, sometimes this is not possible and one fixed schedule must be aggregated from the probabilistic results. The following describes an approach of enumerating and filtering *schedule options* and evaluating those schedule options on their performance.

If all decision variables in an $n \times m$ assignment problem have a non-binary probability, so $\{ \forall x_{ij}: x_{ij} \in]0,1[\}$, there are a total of 2^{nm} possible combinations before constraining the solution space. For a relatively simple problem of assigning 10 elements to 2 locations this gives over a million possible decisions. It is therefore critical to limit the space of solutions such that decision-makers can consider the costs, benefits, and trade-offs of different alternative solutions. The proposed heuristic requires subjective input on thresholds and error tolerances, as well as external requirements not represented in the optimization model.

In each iteration of the heuristic there are six parts:

1. Run the Monte-Carlo simulation for the generalized assignment problem. Generate Bernoulli parameters p_{ij}.
2. Assign element i to location j when the probability of optimally assigning i to j is larger than or equal to a threshold V. Mathematically this is written as

$$p_{ij} \geq V \Rightarrow x_{ij} = 1, \ \forall(i,j) \tag{3-2}$$

3. Not assign element i to location j when the probability of optimally assigning i to j is smaller than or equal to a threshold W. That is

$$p_{ij} \leq W \Rightarrow x_{ij} = 0, \ \forall(i,j) \tag{3-3}$$

4. Restrict the number of elements to be performed by location j. Since it is assumed that X_{ij} follows a Bernoulli distribution with parameter p_{ij}, the sum of n such variables with different parameters follows a Poisson binomial distribution with a mean $\mu_j = \sum_{i=1}^{n} p_{ij}$ and variance $\sigma^2 = \sum_{i=1}^{n} p_{ij}(1 - p_{ij})$. In other words, the expected number of elements performed by location j when schedule is optimized is the sum of the probabilities of each element being assigned to the location. Defining a scalar U, the number of elements to be assigned to location j can be restricted to a range of U standard deviations from the expected number of elements:

$$\sum_{i=1}^{n} p_{ij} \pm U\sqrt{\sum_{i=1}^{n} p_{ij}(1 - p_{ij})}, \ \forall j \tag{3-4}$$

5. Include other requirements. In application, there may be specific requirements that restrict the solution space further. An example from vessel terminal assignment is when a vessel can only be scheduled at a subset of terminals due to size of vessel, equipment available, labor contracts, or other reasons.
6. Evaluate the size of the problem, i.e. the number of schedule options after filtering in steps 2-5. If the number of feasible solutions is lower than a threshold, T, evaluate all feasible solutions. Otherwise repeat steps 1-5, adding constraint to represent the assignments and other filtering made.

The goal of the filtering is to produce a number of schedule options that are evaluated against the random inputs (A_{ij}, B_j, C_{ij}) as discussed in the following paragraphs.

The optimization and simulation and subsequent filtering results in a number of *schedule options*. This part evaluates the schedule options against the random inputs, fitted from historical data, and records the outputs in terms of system cost and other performance measures. This is again done by Monte-Carlo simulation. However, a difference from the previous is that each schedule option is considered fixed and not optimized for every sample of inputs. The purpose is to examine trade-offs between different objectives, including ones the schedule is not optimized for, as well as providing decision makers with alternatives. This adds value to recommendations from analysis by buffering against a single optimal solution being operationally infeasible due to a factor not included in the mathematical model.

Figure 3-1 summarizes the steps and data inputs to the approach. The optimization model is built from requirements and iterated in a Monte-Carlo simulation using probabilistic inputs. The space of schedule options is filtered based on some thresholds which creates new requirements/constraints for the optimization model. Finally when the number of schedule options is under a threshold, they are evaluated against the random inputs and performance and trade-offs of the various schedule options examined.

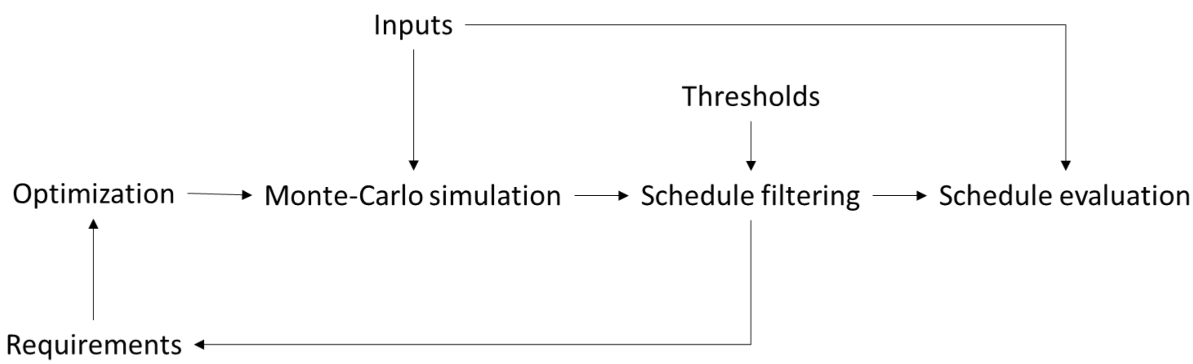

Figure 3-2. Approach to scheduling using the generalized assignment model with uncertain inputs using optimization, simulation, and filtering of solutions.

Metrics

This section develops metrics that quantify disruptions of schedules. The disruption is quantified by comparison of system performance in different scenarios. When system performance is represented by distributions, statistics offer a number of approaches to compare two result profiles. Two-sample unpaired t-test is used to test difference in performance means and Levene's test can be used to test difference in performance variances between scenarios. Furthermore, a visual inspection of histograms can provide insight into the differences between scenarios.

The disruption of the scenarios to the baseline schedules is measured by comparison of system performance. System performance from a simulation can be represented by (i) multisets or (ii) distributions.

A multiset is an extension of the conventional set, where elements can occur multiple times. The notation adds a superscript to the elements, indicating their multiplicity in the multiset. Thus, the set $\{a_1, a_1, a_2, a_3, a_3, a_3\}$ is equivalent to the multiset $\{a_1^2, a_2, a_3^3\}$. In general, a multiset is a 2-tuple $(A, m) = (A = \{a_1, \dots, a_n\}, \{m(a_1), \dots, m(a_n)\})$ where A is a set of the unique elements in the multiset and $m: A \to \mathbb{Z}_{\geq}$ is a mapping from A to the non-negative integers denoting the multiplicity of each. The notation is convenient for sets with high multiplicity of relatively few elements. The common set operations, such as inclusion, addition, union, and intersection can be defined for multisets. For the purposes of this dissertation, we define the *union* ($\cup_M$) of multisets (A, m_A) and (B, m_B) as the 2-tuple $(A \cup B, \max(m_A, m_B))$ where $\cup$ is the union operator from conventional set theory. Similarly, the intersection ($\cap_M$) is defined as $(A \cap B, \min(m_A, m_B)$.

Now, let A_M and B_M be multisets of possible outcomes for two different scenarios. The purpose of quantifying disruption is to describe to what extent a scenario changes outcomes in ways that are distinguishable from the baseline. Multiset A_M contains possible outcomes in the baseline scenario and B_M contains possible outcomes in the disruptive scenario. A disruption coefficient, $D(A_M, B_M)$, should have the following properties:

- $D(A_M, B_M) = 0$ when the sets of possible outcomes (A_M and B_M) are identical.
- $D(A_M, B_M) = 1$ when the sets of possible outcomes (A_M and B_M) are disjoint.
- $D(A_M, B_M) = k \in [0,1]$ when the proportion of possible outcomes B_M that are not shared with possible outcomes A_M is k.

These properties are satisfied by the following definition

$$D(A_M, B_M) = 1 - \frac{|A_M \cap_M B_M|}{|B_M|} \tag{3-5}$$

In cases where possible outcomes are a finite set of real numbers, it may be natural to round outcomes, or bin them, such that an intersection is meaningful. The intervals to which outcomes are rounded (or size of bins) depends on each problem and should be carefully chosen. The result of this procedure can be visualized in a histogram. An example is given in Figure 3-2. The dark shaded are is the intersection of the orange and the blue outcome sets. If blue is the baseline scenario, the disruption is quantified by the area of the lighter orange.

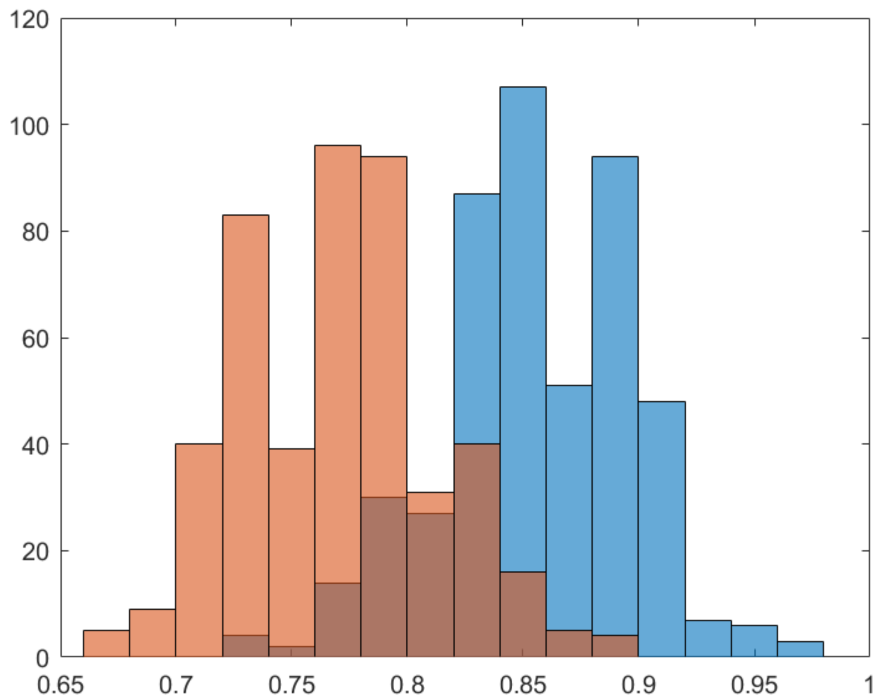

Figure 3-3. Histogram representation of a disruption coefficient. The proportion of the blue area to the total of the blue and shaded area is the value of D.

Alternatively, a probability distribution can be estimated using a kernel density function. A kernel density function is a continuous, non-parametric estimation of the probability density of a random variable (Wand & Jones, 1995). It is estimated from a sample of observations $(x_1, \ldots, x_n)$, a smoothing function K, and a bandwidth h. The density, $\hat{f}$, is then defined by the equation:

$$\hat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right) \tag{3-6}$$

In the demonstration, the smoothing function is selected to be normal distribution function. This is appropriate due to many output variables being close to normal, in addition to convenient mathematical properties (Silverman, 1986). In this case, the bandwidth that minimizes the integrated mean square error has been shown to be (Silverman, 1986):

$$h = \left(\frac{4\hat{\sigma}^5}{3n}\right)^{1/5} \tag{3-7}$$

Using a kernel density function, the histograms are extended to a smooth, continuous function. Figure 3-3 demonstrates the kernel density functions of the same two samples as in Figure 3-2. Both methods, histograms and kernel densities, are dependent on the bin width/bandwidth, so one is not objectively better than the other. In the demonstration, kernel density is used since a continuous function makes comparison across performance measures and scenarios more natural, rather than bin sizes of various units.

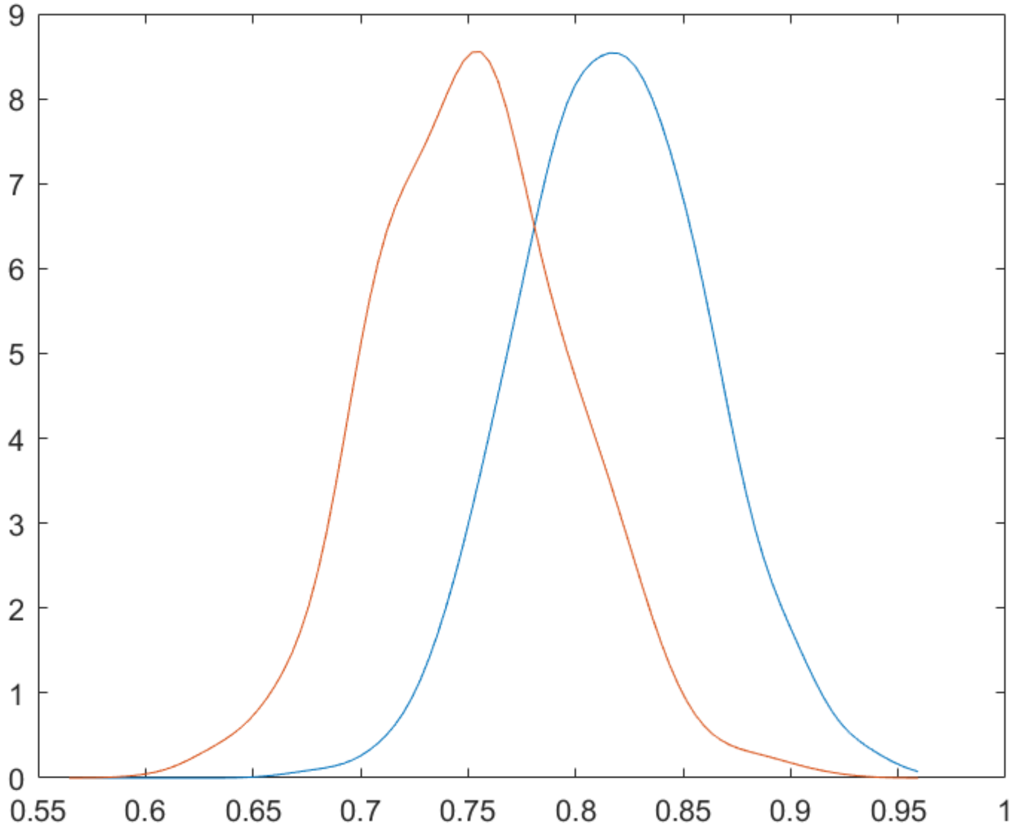

Figure 3-4. Kernel density estimation of two samples. The disruption coefficient is measured as the lack of overlap between the two distributions.

The disruption coefficient can be interpreted as the long-run proportion of observations of scenario B that fall outside normal conditions for scenario A. Alternatively, it is the extent to which it is possible to distinguish scenario B from scenario A for a particular performance measure. It is formulated to only take values between 0 and 1. A disruption of 0 means that there is no discernable difference between the performance for scenarios A and B. A disruption of 1 means there is no overlap of the probability mass functions and any observation would distinguish the scenarios.

In many cases, system performance can be observed while little is known about inputs and transfer functions. This includes many human decision processes, where decision makers can state their priorities under different scenarios, but modeling their transfer functions between inputs and outputs is difficult or impossible. In part, the disruption coefficient remains valid for the special case of schedules where historical probability distributions or system performance or not known. Kendall tau distance (Croux & Dehon, 2010) measures difference between two ordered lists. It counts the number of pairwise disagreements between the lists. Normalizing the Kendall tau distance with the total number of pairwise comparisons yields a disruption coefficient for ordered lists that adhere to properties a.-c.

An advantage of the disruption coefficient is that it does not require the two performance samples to be paired. Many common measures, most notably Euclidean distance, require a pairing of elements from each sample. Pearson correlation requires equal sample size. By using set cardinalities and probability distributions, the disruption coefficient is not limited to paired situations. This is a useful property, since disrupted outcomes can be observed at a different time than the baseline outcomes.

Modeling from multiple perspectives brings the benefits of a fuller understanding of the different trades made by various stakeholders and decision-makers. The disruption coefficient can similarly be used to quantify discrepancies between schedules results from different strategies or modeling perspectives. The disruption can thus be compared both across emergent and future conditions, as well as perspectives. The results of the comparison of schedules and evaluation of disruption measures across emergent and future conditions provide guidance to where to focus data collection and risk analysis.

Significance of coefficients

Several statistical tests are available for the comparison of probability distributions. Typically, they test the null hypothesis that the location (such as mean, median) or scale (such as variance) of two distributions are equal. The family of t-tests tests whether two samples have significantly different means with the assumption of normality of distributions. The Mann-Whitney U test (also known as Wilcoxon rank-sum test) tests the difference between means of two distributions with a normality assumption. Examples of test for equivalence of variances are the F-test and Levene's test.

The Kolmogorov-Smirnov test is commonly used in two instances (Filion, 2015; Olea & Pawlowsky-Glahn, 2009; Young, 1977). One is to test whether a sample comes from an underlying reference distribution and the other to test whether two samples come from the same (unknown) underlying distribution. The latter instance can be used to evaluate the significance of disruption coefficients. The idea is that a disruption changes the disruption, whether in terms of location, scale, or shape. The Kolmogorov-Smirnov, unlike the tests mentioned earlier, test capture differences in all those terms and can therefore be appropriate to test whether the baseline and the disrupted distribution are significantly different. The test statistic is defined as

$$D_{KS} = \max(|\hat{F}_1(x) - \hat{F}_2(x)|)$$

In the context of the disruption coefficient and this dissertation, the hypothesis tested are

- H_0: Baseline output and disrupted output come from the same underlying distribution (no disruption).
- H_1: Baseline output and disrupted output do not come from the same distribution (disruption occurs).

In the results later in this dissertation, the Kolmogorov-Smirnov test is performed to evaluate the significance of the disruption coefficient. A level of significance of 0.05 is used and results where null hypothesis cannot be rejected will be marked with an asterisk (*).

Data collection

This section describes how results from analyzing disruptions of schedules guide further data collection and resource allocation. The framework enables the comparison of disruptions of emergent and future conditions from different domains. It does not require the elicitation of probabilities or monetization of consequences. The disruption coefficient for different disruptions can be useful to direct information collection and analysis on particular emergent and future conditions. If a combination of conditions is found to disrupt the schedule to a significant degree, or a higher degree than another combination, investment in knowledge collection about that disruption could be recommended. The knowledge can then support risk mitigation, risk transfer, or risk acceptance.

Modeling is inherently an incomplete representation of some phenomena. Scheduling for multiple perspectives addresses an aspect on uncertainty called ambiguity, or multiple knowledge frames, by some researchers (Brugnach and Ingram 2012; Brugnach et al. 2008). Scheduling for various emergent and future conditions addresses uncertainty about future states, including deep uncertainty (Maier et al. 2016; Lambert et al. 2012). In the age of big data, there is a need to more explicitly account for the data uncertainty, uncertainty pertaining to the data that populates the models. Data on large-scale infrastructure systems are often originally collected for a specific purpose but later used for various other purposes to cut time and cost of extensive data collection. In practice, these uncertainties do not always fit naturally into existing classification schemes. For example, incomplete data, where some fields are missing, presents a challenge of uncertainty.

Missing data values are sometimes estimated by extrapolating adjacent values or not included in the analysis.

This task result in recommendations to system owner/operators. They give directions for another iteration of the methods by focusing efforts on emergent and future conditions that have the greatest disruption potential, and track uncertainties throughout the life of the analysis.

Summary

The chapter has provided a methodological framework for modeling schedules with probabilistic inputs and disruptions of operations, perspectives, and time frames. The framework will guide the following chapters that demonstrate the methods on case studies from a maritime container port.

Chapter 4

Demonstration: Systems scheduling

Overview

This chapter describes the background and system analysis for the case studies in Chapters 5-8. As described in Table 4-1, it starts with an overview of maritime container port operations, describing business processes, schedules, stakeholders, and related uncertainties before honing in on the vessel berth scheduling task (Thorisson et al. 2019a). An extension of the generalized assignment model allocating vessels to berths is formulated and a baseline schedule is modeled and results analyzed (Thorisson et al. 2019b). The baseline schedule will serve as a starting point for Chapters 5-7, where disruptions are introduced.

Table 4-1. Overview of Chapter 4, describing container vessel scheduling at the Port of Virginia.

Chapter objective	Overview of port operations, scheduling activities, and formulation of baseline vessel berth schedule model
Motivation	Opportunities for improving scheduling in marine container ports by modeling and simulation
Approach and data	Mixed-integer linear programming and Monte Carlo simulation for schedule modeling
	IDEF business process modeling for system analysis
	Operations data from 2016-17 from the Port of Virginia, including sample schedules and vessel arrival and service information
Contributions	Probabilistic scheduling for vessel berthing
	Disruption coefficient as risk impact measure to business process modeling

Background

Port operations and schedules

This section describes a maritime container port from a systems view. It identifies main stakeholders, system schedules, milestones in the movement of containers through the port, schedules, and pertaining uncertainties, as illustrated in Figure 4-1. The process is described for a container arriving by vessel and departing by truck or train but the reverse process is similar. When a vessel arrives and is berthed, the container is unloaded and moved to the stacks where it sits until picked up by a truck or loaded on a train that transport it to destinations in the hinterland of the port.

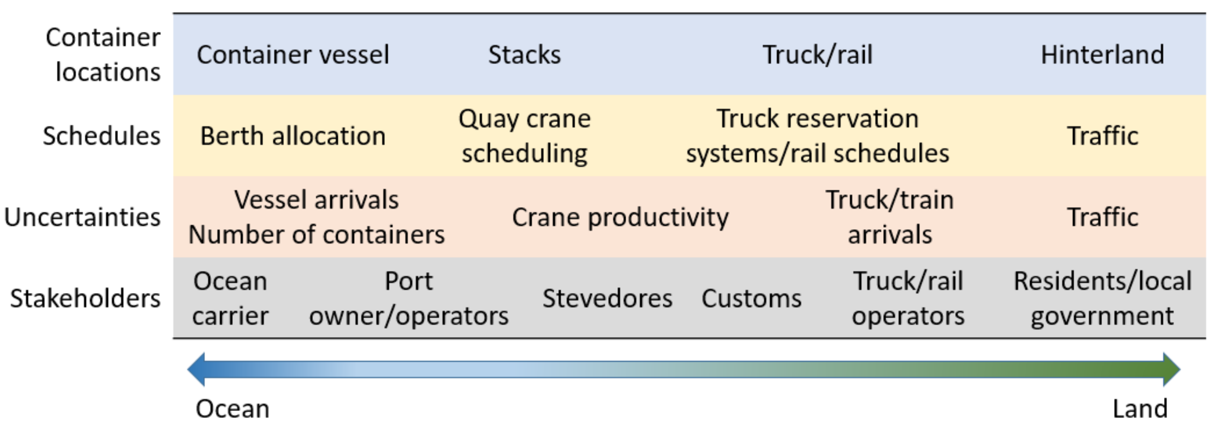

Figure 4-1. Process diagram of the movement of a container through a marine port, describing major location milestones, stakeholders, schedules, and uncertainties.

The schedules that impact the cost and efficiency of the process are allocations of berth at particular terminals to each vessel, the work scheduling of quay cranes that move the container from vessel to dock, and schedules of rail and truck services. The creation of these schedules require balancing the preferences of different stakeholders: port owners/operators, ocean carriers that operate the container vessels, and stevedores who provide the necessary labor to handle operations. These stakeholder have different, sometimes competing objectives:

- Port owners/operators want to create revenue by utilizing resources in the most cost-effective manner and be competitive with other ports. In many cases, ports are under public ownership and in addition to creating profit serve to stimulate economic growth in their region by attracting industry and services that rely on stability in imports and exports.
- Ocean carriers operate the vessels carrying containers between ports. Their main objective during a port call is that berthing time is as close to their arrival. Idling is both consumes fuel and has cascading effects on the vessels route. Handling time, how long it takes for containers to be unloaded from the vessel and others to be loaded on, is another important objective of ocean carriers. Furthermore, if a carrier has multiple vessels calling at the port, it can be desirable that they all berth at the same terminal.
- Stevedores, often represented by labor unions, provide the landside labor. They operate cranes and other equipment that moves containers from vessel to dock. Stevedores value regularity in work schedules, overtime payments when working long shifts, and others. Stevedores typically contract with the port operator rather than the ocean carrier.
- Customs officers are responsible for clearing imports and exports shipped through the port to or from foreign countries.

- Truck and rail operators receive the containers from the stacks and transport them to warehouses, factories, intermodal facilities, and other hinterland destinations. Truck congestion at container port has been a problem at ports worldwide and a primary objective is to relief congestion at terminal gates and yard and shorten truck turn times.
- Hinterland residents live in close proximity with the port and/or transportation corridors utilized by trucks and trains engaged in port activities. While a port can create jobs and other economic benefits, adverse environmental effects, air and water quality, traffic congestion, noise pollution, and others can be of concern to the general public in the vicinity of a port.

The creation of schedules for vessel berthing, quay crane assignments, and truck and rail services is achieved in various ways. Many methods are used in practice and even more have been proposed by researchers. Stahlbock and Voss (2008) describe the various applications of operations research in container terminal operations. The following summarizes practices and available methods.

– Vessel berth schedules are the result of negotiations between port operators, ocean carriers, and stevedores. Since the 1990's, operations researchers given much attention to the "berth allocation problem", and developed methods and algorithms for a variety of optimization objectives, constraints, layouts. Bierwirth and Meisel (2015) provide a literature survey of berth allocation literature.
– Quay crane assignment and scheduling have been studied by operations researchers as well (Stahlbock & Voss, 2008). In practice they are more often achieved through negotiations between port operators and stevedores and institutional learning and knowledge. Crane

assignment and berth scheduling are interacting processes and research has studied the coupled of the two.

- Different scheduling approaches for trucks receiving and delivering containers at ports exist in practice. Traditionally, terminals have been open during daytime business hours and trucks have come and gone when convenient for them. In recent years, increased demand and terminal congestion have prompted port operators to open earlier and close later or keeping terminals open 24 hours a day for truck services. Reservation systems are also becoming common, with the first one piloted in the ports of Los Angeles and Long Beach in 2005. Various implementations exist, but typically a limited number of reservations are available for time slots of 60-120 minutes. As these systems are still relatively new, some ports (e.g. New York-New Jersey, Norfolk) only require reservations during the busiest hours of the day (morning), with plans to expand to longer periods or only accept trucks with reservations.

The reliability of schedules is of importance to all stakeholders. However, various uncertainties create a challenge to create schedules that are both efficient in ideal operating conditions but yet robust to fluctuations and resilient to larger disruptions. Among the most impactful uncertainties are the time of vessel arrival, the number of containers to be unloaded/loaded, and crane productivity:

- Ocean carriers typically provide services between continents or regions, serving multiple ports along the way. They often have scheduled weekly or bi-weekly arrival times at each port. However, due to weather, technical issues, fluctuations in demand, customs clearance, and other factors, the arrival times are in practice highly variable. It is not uncommon for a vessel to arrive 24-48 hours before or after their scheduled arrival.

- The number of containers handled at each port, which ultimately contributes to arrival and departure times, fluctuates based on the demand for products in the ports impact area, production cycles in exporting countries, and other factors. For example, the demand depends on the season of the year, with imports increasing around holidays, exports increasing during seasons of harvest, etc.
- Quay crane productivity presents a significant source of uncertainty. Breakdowns, labor skill level, weather, and stowage of containers on the vessel are among factors that affect the productivity of state-of-the-art cranes which can run from 15 to 40 containers moved per hour.
- Truck arrivals have historically been relatively unpredictable. Drivers traveling short distances, e.g. to local or regional warehouses, tend to start arriving early in the morning to be able to complete 3-5 trips during terminal hours. With reservation systems being implemented, truck arrivals should become more predictable and evenly distributed throughout operating hours. However, hinterland traffic, road construction, accidents, and other factors can cause drivers to miss their reservations and policies are still being developed on how to handle such cases.

Berth allocation

The focus of this and subsequent chapters is on the berth allocation process. There is a gap between the theory and methodology of the berth allocation problem in operations research and container port industry practices. Specifically, the complexity of stakeholder preferences and interactions, variability between port layouts and specifications, and uncertainties about future demands limit the applications of optimization methods in practice. Figure 4-2 illustrates the main factors (parameters, stakeholders, uncertainties, planning horizons, and available methods).

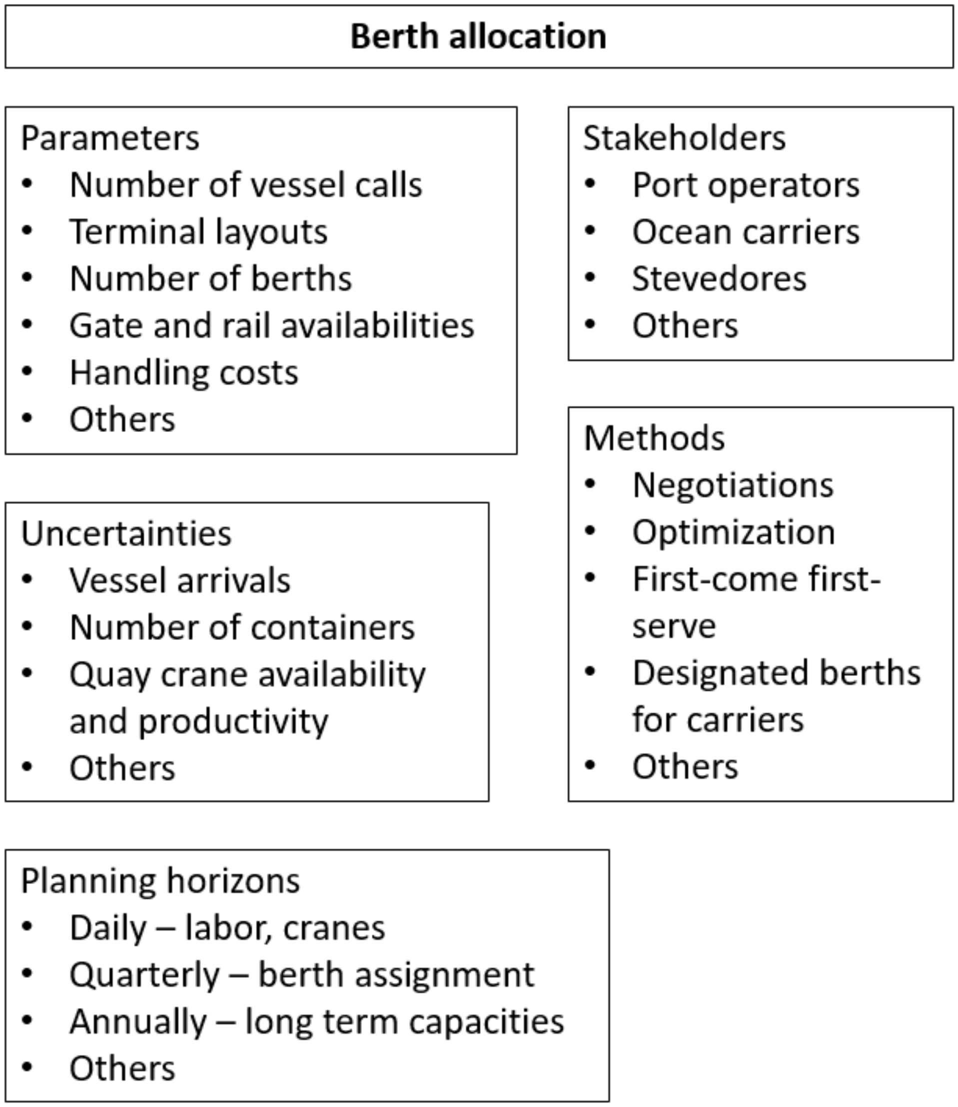

Figure 4-2. Summary of factors influencing the berth allocation process: Scheduling vessels to a location and time at a container port.

The framework proposed here uses methods from operations research and simulation but adjusts recommendations to account for factors not included in the mathematical model. It provides a prioritization of vessels, performance measures, and disruptive scenarios that should be considered by stakeholders while negotiating on schedules. Figure 4-3 gives an overview of the layers of the framework and related recommendations. A deterministic mixed-integer linear program to solve the berth allocation problem for a fixed set of inputs provides the first layer. The second layer adds distributions, based on historical data, to inputs which results in different optimal solutions for different combinations of input values. This allows for the evaluation of robustness of berth assignments for various vessels: e.g. a vessel that is optimally berthed at a particular location in 90% of iterations has a more robust assignment than a vessel that is optimally placed in one location 50% of iterations and another location 50% of iterations. The third layer defines scenarios that represent emergent and future conditions, different from those covered by historical data, or conditions that have potential to surprise stakeholders. This allows for comparison of robust vessel assignments and other performance measures with and without the influence of the scenarios.

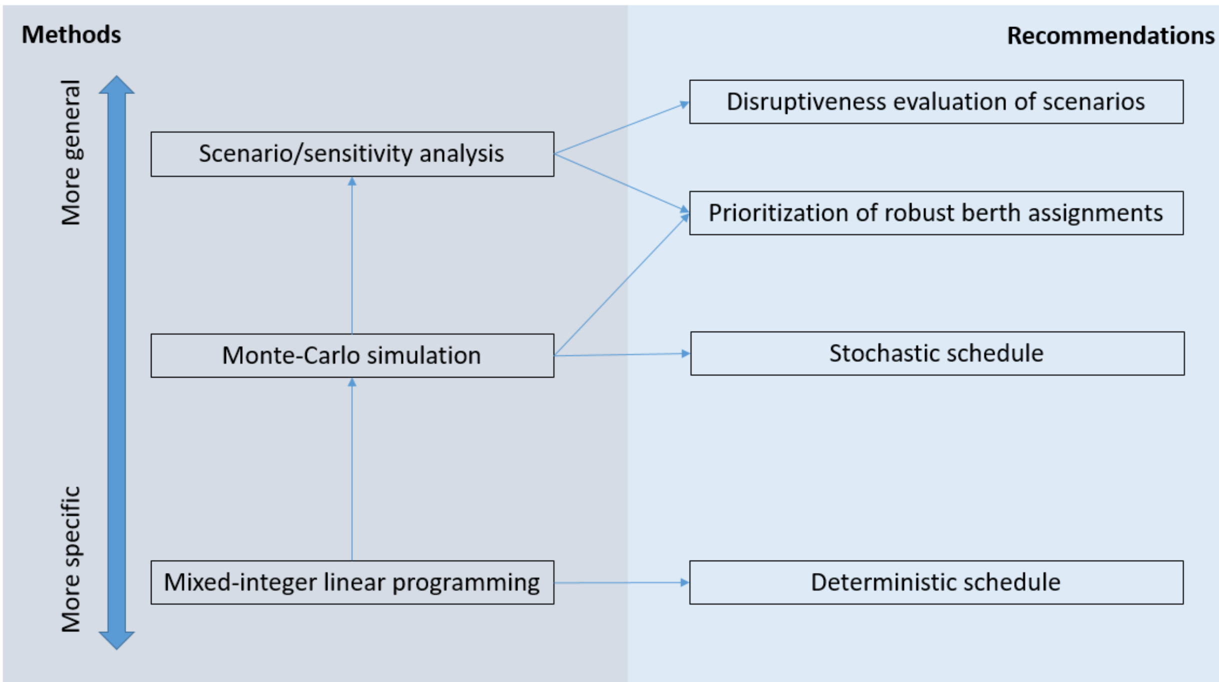

Figure 4-3. Layers of methods and recommendations of a framework for vessel scheduling at a container port.

Port of Virginia

Maritime container ports are a critical node in global supply chains as transportation of goods over long distances is in large part carried out by cargo vessels (Buxbaum, 2016). The ports need to operate through disruptions at global levels (climate, macroeconomic trends, technological innovations, etc.) and regional levels (extreme weather events, local-level funding, demographic shifts, seasonal supply and demand). In 2017, major ocean carriers formed new alliances, sharing resources and services (American Export Lines, 2017). This requires negotiations between ports and carriers on schedules. Port authorities are concerned with avoiding congestion at their facilities and cost-efficient equipment usage while carriers want to minimize time spent waiting for and receiving service at ports of call. Vessel services are typically planned to make weekly stops at each port. Schedules are typically negotiated for time horizons of months or years and it is therefore important that they are resilient to various disruptions, such as weather events, fluctuations in container volume, planned construction and maintenance activities, and others. The results contribute to robust scheduling and recommendations for preparedness to specific conditions (Thorisson et al. 2018).

The Port of Virginia (Virginia Port Authority, 2018) is a major port on the East Coast of the United States. It serves the Commonwealth of Virginia and other states the Mid-Atlantic region, as well as reaching inland destinations in the Midwest and Southeast via rail connections. Over a third of its cargo arrives and departs by rail, the highest share among East Coast ports (iContainers, 2015). There port is composed of six facilities, four in the Hampton Roads region, one in Richmond, and one in Front Royal:

– Three container terminals: Norfolk International Terminals (NIT), Virginia International Gateway (VIG), and Portsmouth Marine Terminal (PMT)

– One designated break-bulk and roll on/roll-off terminal: Newport News Marine Terminal (NNMT)

– One inland barge terminal: Richmond Marine Terminal (RMT)

– One truck/rail intermodal container transfer facility: Virginia Inland Port (VIP)

In addition, there are plans to build a new marine terminal, Craney Island Marine Terminal, in the Hampton Roads. Figure 4-4 gives an overview of the facilities and their locations in the Commonwealth.

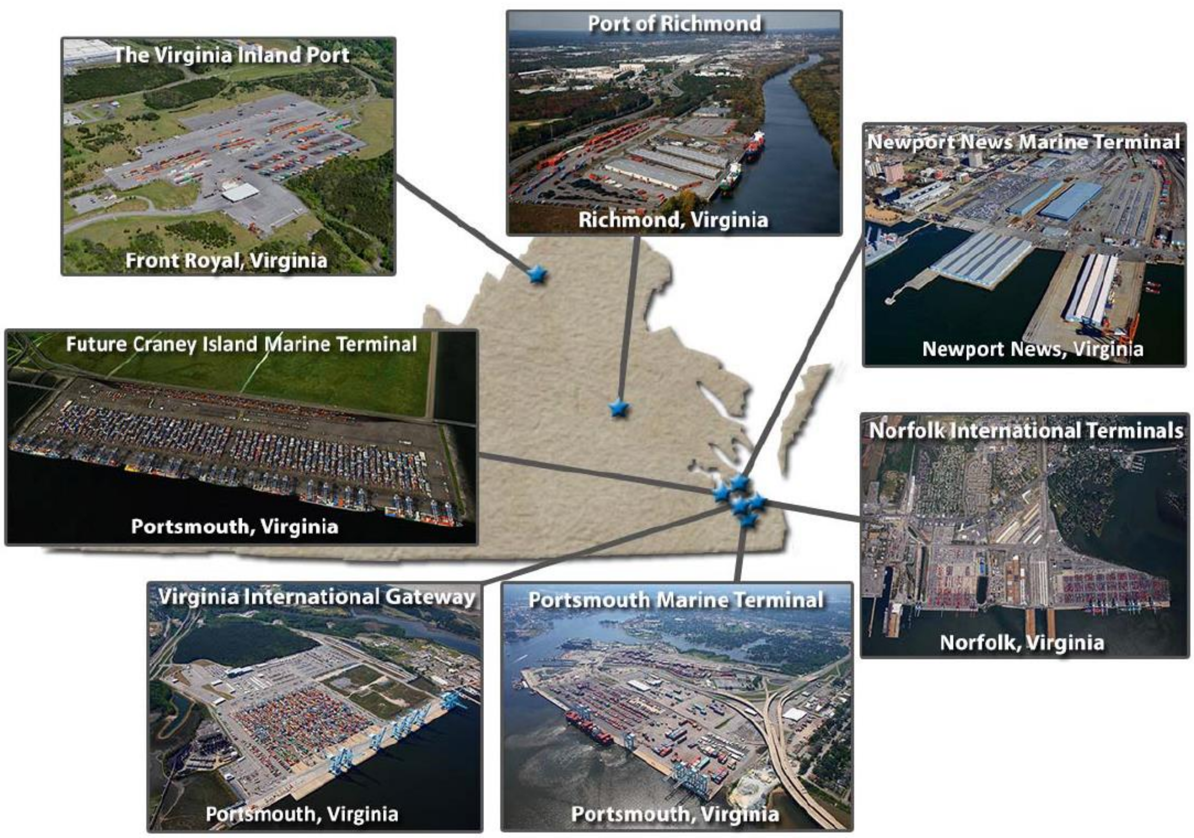

Figure 4-4. Facilities of the Port of Virginia and their locations in the Commonwealth of Virginia (Port of Virginia, 2015).

Technical approach

Business process modeling

Lambert et al. [2006] describe a methodology that integrates risk identification and business process modeling through an extension of IDEF modeling that incorporates sources of risk in business processes. This methodology is built on the well-known IDEF modeling. Figure 4-5 shows the fundamental elements of IDEF represented by boxes and connecting arrows. A box is used to represent an activity where the meaning of the arrows varies depending on where they point to. The meaning of the four arrows used in this methodology is as follows [O'Donovan et al. 2005]:

- *Input*: describes the objects or data that are transformed by the activity into output
- *Output*: describes the objects or data produced by an activity
- *Control*: describes the conditions needed to produce correct output
- *Mechanism*: describes the means used to perform an activity.

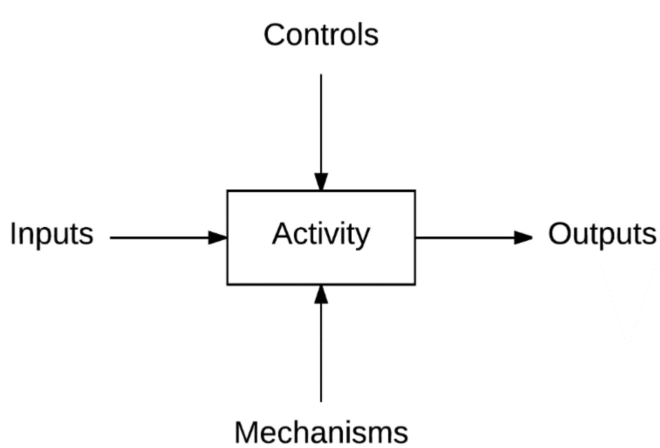

Figure 4-5. IDEF modeling format to be extended by adding sources of risk and disruption potential.

Now, let A represent the set of activities in the IDEF model:

$$a_k, \qquad \text{where } \{k = 1, 2, \ldots, K\} \tag{4-1}$$

The subscript k is used here to represent a unique index of an activity, while K represents the total number of activities included in the IDEF model. Since the total number of inputs, controls, mechanisms, outputs, sources and disruption potentials of risks can be different from one activity to another, each n in the following sets will have a different subscript k.

Let W represent the set of inputs of an activity in the IDEF model:

$$w_{k,i}, \qquad \text{where } \{i = 1, 2, \ldots, n_k^w\} \tag{4-2}$$

The subscript i is used to represent a unique index of an input for activity a_k, while n_k^w is used to represent the total number of inputs for activity a_k.

Let C represent the set of controls of an activity in the IDEF model:

$$c_{k,j}, \qquad \text{where } \{j = 1, 2, \ldots, n_k^c\} \tag{4-3}$$

The subscript j is used to represent a unique index of a control for activity a_k, while n_k^c is used to represent the total number of controls for activity a_k.

Let M represent the set of mechanisms of an activity in the IDEF model:

$$m_{k,l}, \qquad \text{where } \{l = 1, 2, \ldots, n_k^m\} \tag{4-4}$$

The subscript l is used to represent a unique index of a mechanism for activity a_k, while n_k^m is used to represent the total number of mechanisms for activity a_k.

Let Z represent the set of outputs of an activity in the IDEF model:

$$z_{k,p}, \qquad \text{where } \{p = 1, 2, \dots, n_k^z\} \tag{4-5}$$

The subscript p is used to represent a unique index of an output for activity a_k, while n_k^z is used to represent the total number of outputs for activity a_k.

Since the output of any IDEF model depends mainly on the type of activity, inputs, controls, and mechanisms associated with this activity (as can be seen in Figure 1) and from the above described algebraic representation, the output function *h* of any activity can be written as:

$$h: A \times W \times C \times M \rightarrow Z \tag{4-6}$$

Unfortunately, this formulation of the output function ignores the possible disruptions of an activity. These disruptions can be described as sources of risk. In order to account for the different sources of risk that disrupt the activity, the methodology developed by Lambert et al. [2006] added a fifth arrow pointing to the clipped lower-left box corner as can be seen in Figure 4-6.

Let *S* represent the set of sources of risk of an activity in the IDEF model:

$$s_{k,q}, \qquad \text{where } \{q = 1, 2, \dots, n_k^s\} \tag{4-7}$$

The subscript q is used to represent a unique index of a source of risk for activity a_k, while n_k^s is used to represent the total number of sources of risk for activity a_k.

After the introduction of the sources of risk *S*, the output function *h* can be rewritten as follows:

$$h: A \times W \times C \times M \times S \rightarrow Z \tag{4-8}$$

With this modification, the output of the IDEF model not only depends on the type of activity, inputs, controls, and mechanisms, but also depends on the sources of risk associated with the activity.

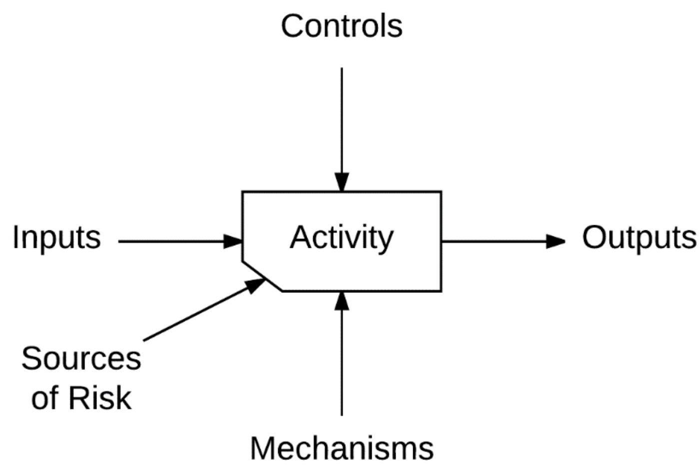

Figure 4-6. Modified IDEF modeling format with risk identification incorporated.

Although the above-described methodology accounts for the sources of risk, it fails to consider the potential disruptions associated with such risks. To improve this methodology, a sixth arrow originating from the clipped upper-right box corner and pointing outward is added as can be seen in Figure 4-7.

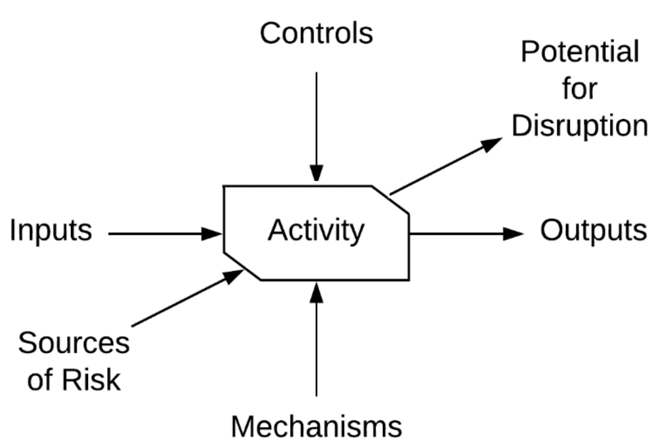

Figure 4-7. Modified IDEF modeling format with risk identification and disruption potential incorporated.

Let Y represent the set of disruption potential to an activity in the IDEF model:

$$Y_{k,r}, \qquad \text{where } \{r = 1, 2, \ldots, n_k^y\} \tag{4-9}$$

The subscript r is used to represent a unique index of a disruption potential (due to a source of risk) for activity a_k, while n_k^y is used to represent the total number of disruption potentials for activity a_k.

After this modification, the output function can be written as follows

$$h: A \times W \times C \times M \times S \rightarrow Z \times Y \tag{4-10}$$

The risk assessment approach is presented in four parts. First is *deterministic scheduling*, formulating a policy to create schedules with fixed inputs. Second is *stochastic scheduling*, where inputs are modeled as random variables to account for historical variability. The third part is *risk identification*. Sources of risk are not always represented in historical data. The fourth part evaluates the *schedule disruption* potential of each of the identified sources of risk and introduces measures for quantification of disruptiveness.

The modified business process methodology, described earlier in this section, is used as an outline for assessment of schedule disruptions at the port. The IDEF model encompasses three activities: *Service Agreement*, *Berth Allocation*, and *Operations*. These activities have one external input, two internal inputs, five external controls, five external mechanisms, two external outputs, two internal outputs, six sources of risk, and three disruption potentials. Table 4-1 and Figure 4-8 show the business process model incorporating the risk identification.

This demonstration will focus on the *Berth Allocation* process. Of the three business processes, it has a significant analytical component and the greatest opportunity for improvement using systems engineering and risk analysis. The process is controlled by two constraints: the availability of labor and equipment, and service requirements of the ocean carriers. Three mechanisms are used for the scheduling: mixed-integer optimization, simulation, and scenario analysis. The model includes sources of risk that can disrupt the business process, such as temporary capacity constraints, fluctuations in demand, and others. The outputs of the scheduling are used to inform decision making and planning for operations.

Table 4-2. Business process notation used in demonstration of vessel scheduling at maritime container port.

Business process model building block	Example from demonstration
Activity (A)	Berth allocation
Inputs (W)	Service contracts
Controls (C)	Labor and equipment constraints, service requirements
Mechanisms (M)	Optimization, simulation, scenario analysis
Sources of risk (S)	Berth closure, higher container volume
Outputs (Z)	Schedule
Disruption potential (Y)	Disruption measures, quantifying the shift of performance metric distributions

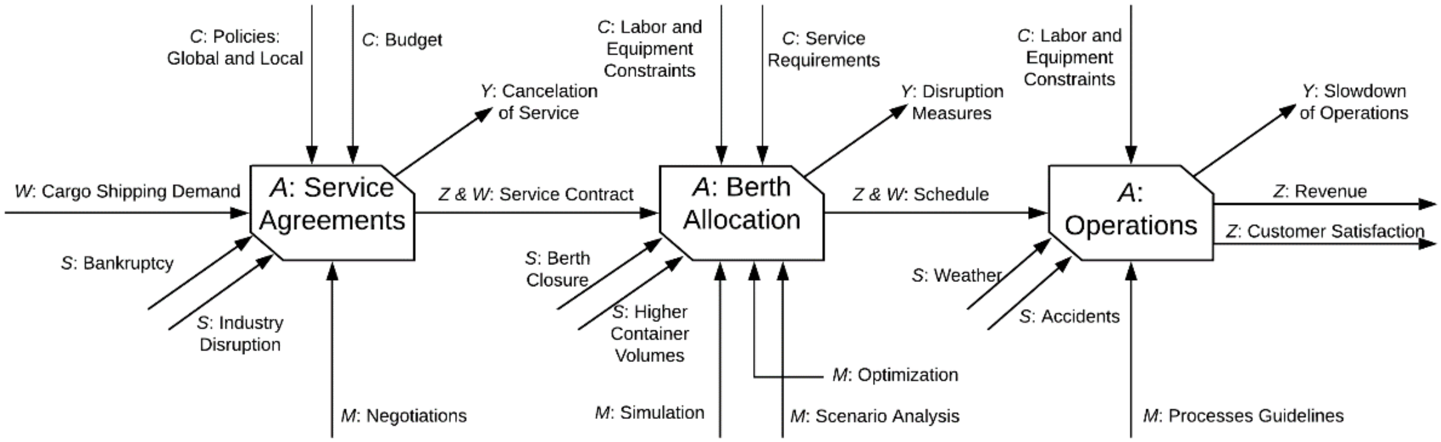

Figure 4-8. Business process model with risk identification of operational level activities at a container port. The letters refer to a building block of business process modeling as described in Table 4-1.

Berth allocation optimization modeling

This section describes a mixed-integer linear optimization to model a schedule. The formulation is presented for berth planning of vessels but can be adjusted to other types of scheduling. The formulation assigns a time and berthing location to each vessel considered for a given time period. Robenek et al. (2012) provide an example of a vessel scheduling mixed-integer formulation which has been modified and extended here. Figure 4-9 provides a sample port layout with multiple terminals. In this case it is assumed that the list of vessels, arrival time, container volume, and handling time is fixed and known. Further inputs are the unit-costs of handling containers by mode of further transportation (truck or rail) at each berthing location. These vary due to different equipment and availability of rail connections. In addition to the berthing time and location, the total cost of berthing vessels, the sum of delays over the time period, and the utilization at each of the locations is recorded. The notation for the optimization problem is described below.

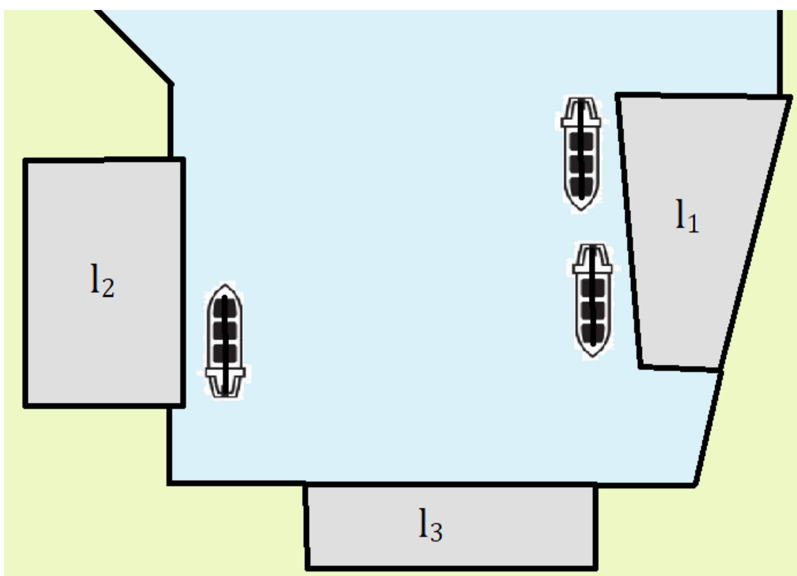

Figure 4-9. Layout of container port. The following sections will describe allocation of a series of vessels to terminals (l_1, l_2, l_3) such that berthing cost is minimized.

Input variables to the model:

- n: identifier of vessel
- t: identifier of time period
- p: identifier of berthing location
- f: identifier of handling modes
- a_n: Requested arrival time of vessel n
- h_n: handling time of vessel n
- TEU_{nm}: number of containers on vessel n of mode m
- g_{pm}: cost per container at location p for mode m
- $c_{np} = TEU_{nm} g_{pm}'$: cost of berthing vessel n at location p
- MAX_p: maximum container volume handled over time horizon at location p

Decision variables:

- x_{np}: x_{np}=1 if vessel n is berthed at position p, x_{np}=0 otherwise
- t_n: berthing time of vessel n
- z_{nk}: z_{nk}=1 if vessel n finishes before vessel k starts, z_{nk}=0 otherwise
- y_{nk}: y_{nk}=1 if vessel n is berthed at a lower indexed position than vessel k, y_{nk}=0 otherwise

System outputs:

- C: total cost of berthing all vessels
- Q: total delays of vessels
- u_p: utilization of location p over the time period

The objective is to minimize the cost of berthing all vessels subject to constraints $(i) - (vii)$:

$$\min_{n,p} c_{np}^T x_{np} = C$$

$$\begin{array}{lll}
\sum_{p=1}^{P} x_{np} = 1 & \forall n & (i) \\
t_k + B(1 - z_{nk}) \geq t_n + h_n & \forall n,k: n \neq k & (ii) \\
l_k + B(1 - y_{nk}) \geq l_n + 1 & \forall n,k: n \neq k & (iii) \\
z_{nk} + z_{kn} + y_{nk} + y_{kn} \geq 1 & \forall n,k: n \neq k & (iv) \\
t_n + h_n \leq T & \forall n & (v) \\
t_n \geq a_n & \forall n & (vi) \\
t_n \leq a_n + \delta & \forall n & (vii) \\
\sum_{n=1}^{N}\left(x_{np} \sum_{m=1}^{M} TEU_{nm}\right) \leq MAX_p & \forall p & (viii) \\
\sum_{n=1}^{N}\left(x_{np} \sum_{m=1}^{M} TEU_{nm}\right) \geq MIN_p & \forall p & (ix) \\
c_{np} = TEU_{nm} g'_{pm} & \forall n,m,p & (x)
\end{array} \tag{4-11}$$

Constraint (i) ensures that each vessel is scheduled. Constraints $(ii) - (iv)$ make sure there is no overlap between vessels, i.e. two vessels are at the same location at the same time, where B is a large integer. It furthermore requires there to be one time period between a vessel leaving a berth and the next being berthed. Constraint (v) requires finishing handling all vessels within the time period. Constraints (vi) and (vii) ensure that vessels are scheduled after their arrival time and no later than a threshold value δ after the arrival time, respectively. Constraint $(viii)$ limits the total number of containers handled at location p during the time period T to value MAX_p. Constraint (ix) requires at least MIN_p containers to be handled at location p during the period. Finally, constraint (x) ensures that the cost of assignments is consistent with the volume as well as the per-unit cost for each mode and terminal.

Vessel berth schedule modeling

The optimization model presented in the previous part assumes that inputs are known and does not include any uncertainty about inputs or outputs. In reality, a number of uncertain factors cause fluctuations in schedules. To account for uncertainty about input variables, Monte-Carlo simulation is integrated with the optimization model. Distributions from historical data are fitted for the input variables: arrival times, handling times, container volume. Drawing randomly from the input distributions, a number of iterations are run which results in output distributions for the system cost, delays, utilizations, and vessel berthing times and locations.

In the modeling of vessel berth scheduling at the Port of Virginia, three variables are considered stochastic for the purpose of the Monte-Carlo simulation: arrival time of each vessel, number of containers to be handled, and the handling time.

Data

This section describes inputs for the optimization model, representing real-world operations data from the Port of Virginia. At first, results are presented for the deterministic case, when inputs are constant. Subsequent sections will cover the stochastic case when inputs are varied to simulate late or early arrivals, variability in cargo volume, and handling time.

Table 4-2 describes the cost to unload a container off a vessel unto its next node of transportation. The cost varies across three modes of transportation: truck, rail company X, and rail company Y. As well, it varies across the three container terminals: NIT, VIG, and PMT. The cost should not be interpreted as a life-cycle marginal cost for the entire organization as it does ignore various costs that are distributed equally across all modes and terminals, e.g. overhead and capital costs. Rather, it reflects the different operational costs between modes and terminals which are realistic when making comparisons between scenarios and operations strategies.

Table 4-3 shows the number of berths and weekly capacity at each terminal. The capacity is set to account for operational constraints in additions to the physical availability of berth space. These include landside operations which share resources with seaside operations, such as labor and equipment requirements to load from stacks to trucks and trains, routine maintenance, and others.

Table 4-4 describes inputs related to each vessel service: estimated number of containers to be handled at the port by mode, requested arrival time, and estimated handling time.

Table 4-5 provides a summary of inputs variables not covered in Table 4-2 to Table 4-4. This includes most importantly the allowed slack time (*delay*) δ, which is the time period, starting at the arrival time, which a vessel must be berthed within. Others are the number of vessels included, number of time periods, number of berthing locations, and modes of further transportation.

Table 4-3. Cost, per container, to unload to the different modes by terminal.

	Truck	Rail X	Rail Y
NIT	$100	$165	$175
VIG	$75	$90	$110
PMT	$130	$155	$300

Table 4-4. Weekly capacity at each terminal, measured in containers per week.

Terminal	Number of berths	Weekly container capacity
NIT	4	20000
VIG	2	17500
PMT	3	10000

Table 4-5. Estimated number of containers by three modes, requested arrival time, and estimated handling time by vessel for deterministic scheduling.

Vessel ID	Containers to trucks	Containers to Rail X	Containers to Rail Y	Requested arrival time	Estimated handling time
n1	163	110	0	33	3
n2	496	0	291	4	4
n3	229	0	134	12	3
n4	800	0	125	16	4
n5	6667	306	27	33	4
n6	152	40	0	34	2
n7	386	0	13	39	3
n8	868	0	509	21	5
n9	2170	0	1274	3	5
n10	930	0	546	28	6
n11	620	0	364	9	12
n12	391	64	400	42	5
n13	995	70	158	36	10
n14	985	0	400	30	5
n15	1180	214	261	9	4
n16	2197	650	1350	30	4
n17	564	260	76	30	4
n18	418	180	17	22	3
n19	526	118	6	23	3
n20	195	15	0	39	2
n21	106	95	3	39	2
n22	365	0	324	42	4
n23	588	14	282	21	4
n24	999	22	478	23	6
n25	183	0	3	26	2
n26	400	600	50	27	4
n27	1488	284	187	15	7
n28	700	300	0	35	4
n29	502	132	0	31	3
n30	205	0	208	3	3
n31	161	0	30	40	2

Table 4-6. Various input variables for berth scheduling optimization.

Symbol	Input variable	Description	Details
δ	Allowed delay	$\delta = 12$ hr	A vessel must be berthed within 12 hours of arrival
n	Number of vessels	$n = 31$	31 vessels are included, each arriving once per week
t	Number of time periods	$t = 48$	Each time period is 4 hours and extends from Sunday to the following Sunday to account for continuity
p	Number of berthing locations	$p = 9$	4 berths at NIT, 2 berths at VIG, and 3 berths at PMT
f	Number of inland transportation modes	$f = 3$	Containers can be moved onto trucks, or transported by either of two rail companies

The arrival times are modeled with a stepwise linear function, fitted on arrival data from January 2015 until May 2017. Figure 4-10 illustrates the distribution. There are a total of 1514 vessel calls taken into consideration.

The number of containers is modeled using a truncated normal distribution for each vessel. The mean of the distribution is an estimate provided by port operators and reflects current requests from the shipping lines. The variance is calculated from historical data, from January 2015 to May 2017. In order to account for differences between the means of the historical data and the estimated mean, the variances are scaled accordingly. A normal distribution can return values from negative infinity to infinity. However, container numbers cannot be negative and are bound from above by the capacity of the vessel and therefore the distributions are truncated to $\pm 30\%$ of the mean.

In the deterministic optimization, handling time was estimated by operators. In this part however, handling times are modeled as a function of the number of containers being handed. Figure 4-11 illustrates the relationship between the number of containers and the handling time, based on the 1514 vessel calls between January 2015 and May 2017. The residuals are shown in Figure 4-12. The residuals have an approximately zero mean and close to constant variance and thus a linear fit is justified. The functional relationship is described by the equation

$$h_n = (0.0099 \sum_m TEU_{mn} + 5.34 + N(0, 3.21))/4$$

Where $N(0, 3.21)$ is a normal random variable with a 0 mean and variance of 3.21.

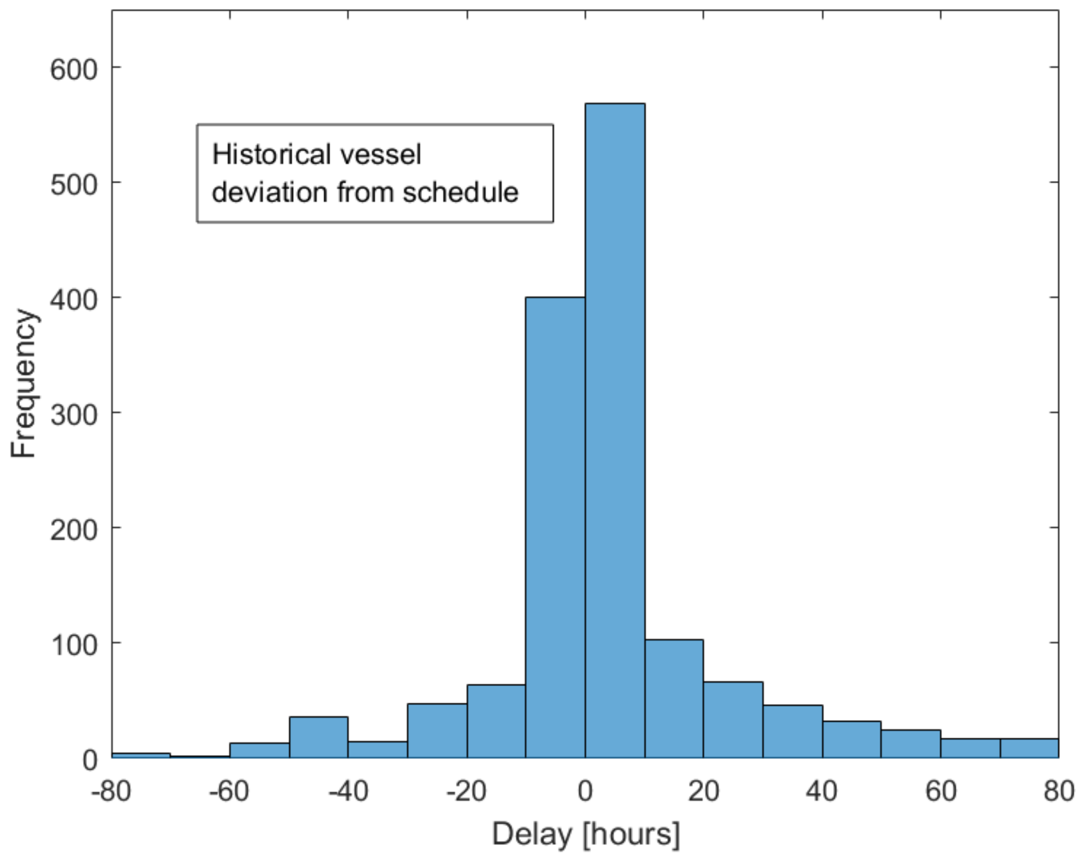

Figure 4-10. Distribution of variations in vessel arrival times, compared to their scheduled arrival.

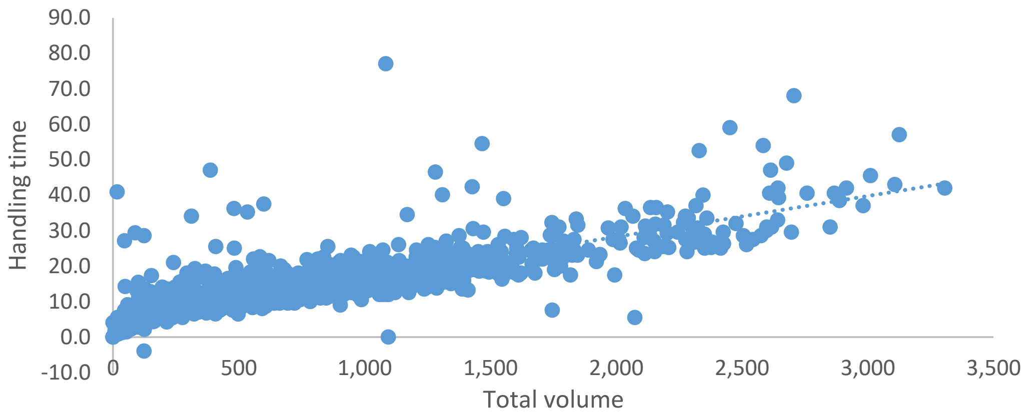

Figure 4-11. Functional relationship between the container volume on a vessel and the handling time.

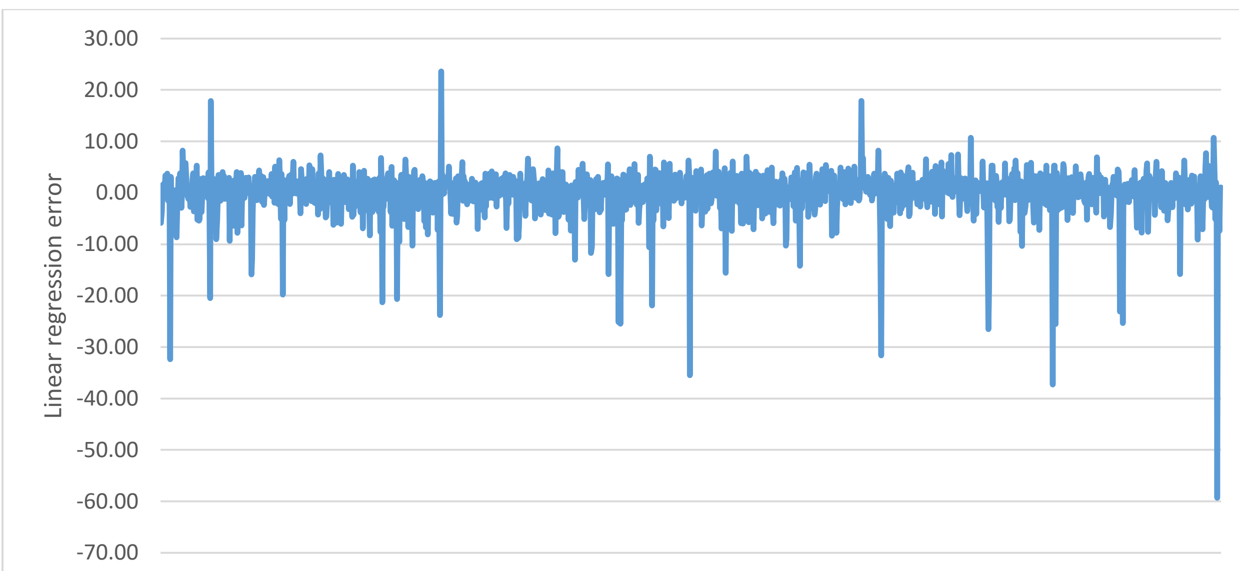

Figure 4-12. Residuals from linear fit of handling time as a function of the number of containers handled.

Results

Table 4-6 shows the deterministic optimization berth schedule. An important result is that one of the terminals, PMT, us unused in this solution. The terminal is the oldest of the three container terminals at Port of Virginia and has the highest cost of operations. In later sections, it will be demonstrated how the terminal is a necessary asset which is utilized when the port is in disrupted states of capacity at other terminals, or when demand for container handling is higher. VIG has the highest utilization of the terminals, which is not unexpected since it has the lowest cost for all three modes. Table 4-7 summarizes system performance for the optimal solution. Performance measures included are total cost, cost per container, system delays, and utilization at each terminal, respectively. The average cost per container of $101 is lower than any mode cost at NIT or PMT, underscoring the importance of VIG, with its automated crane system, to overall system cost. The total system delay of 152 hours comes to an average of 5 hours per vessel. Since a 12 hour delay is allowed by the constraints of the optimization, less than half of the permitted delay time is utilized in the optimal solution.

Table 4-7. Berth schedule as the result of deterministic optimization. The time period is 8 days, one week with an additional day to account for continuity.

	NIT				VIG		PMT
Sunday							
4:00							
8:00				*n9*			
12:00				*n9*		*n2*	
16:00				*n9*		*n2*	
20:00				*n9*		*n2*	
Monday				*n9*		*n2*	
4:00							
8:00					*n15*	*n11*	
12:00					*n15*	*n11*	
16:00					*n15*	*n11*	
20:00					*n15*	*n11*	
Tuesday						*n11*	
4:00						*n11*	
8:00		*n3*				*n11*	
12:00		*n3*	*n4*			*n11*	
16:00		*n3*	*n4*			*n11*	
20:00			*n4*			*n11*	
Wednesday			*n4*			*n11*	
4:00						*n11*	
8:00							
12:00			*n18*			*n23*	
16:00	*n8*		*n18*		*n24*	*n23*	
20:00	*n8*		*n18*		*n24*	*n23*	
Thursday	*n8*				*n24*	*n23*	
4:00	*n8*	*n25*		*n19*	*n24*		
8:00	*n8*	*n25*		*n19*	*n24*		
12:00			*n10*	*n19*	*n24*		
16:00			*n10*				
20:00	*n17*		*n10*		*n16*		
Friday	*n17*		*n10*		*n16*		
4:00	*n17*		*n10*		*n16*	*n14*	
8:00	*n17*		*n10*		*n16*	*n14*	
12:00						*n14*	
16:00				*n1*		*n14*	
20:00			*n6*	*n1*	*n5*	*n14*	
Saturday			*n6*	*n1*	*n5*		
4:00					*n5*		
8:00				*n20*	*n5*	*n13*	
12:00				*n20*		*n13*	
16:00						*n13*	

20:00	*n7*		*n21*	*n13*	
Sunday	*n7*		*n21*	*n13*	
4:00	*n7*			*n13*	
8:00		*n12*	*n22*	*n13*	
12:00		*n12*	*n22*	*n13*	
16:00		*n12*	*n22*	*n13*	
20:00		*n12*	*n22*	*n13*	

Table 4-8. System performance for deterministic optimal solution.

Performance measure	Value
System cost	$3,204,735
Cost per container	$101
System delays	152 hr.
NIT utilization	26%
VIG utilization	62%
PMT utilization	0%

When input variables are treated as stochastic, the resulting berth schedule and performance measures will be described in terms of probability distributions rather than deterministic values. It is thus no longer possible to identify one optimal solution, rather a solution is developed for each random instance of inputs.

Here, the simulation is run for 2000 iterations, each time generating a random combination of arrival times, number of containers, handling times for the 31 vessels. Table 4-8 shows the distribution of berth allocations for each vessel. Note, that since arrival times vary, the representation from Table 4-6 is no longer possible. Instead, the table shows the proportion of iterations where a vessel was allocated to a particular terminal. Out of the 31 vessels, 15 are consistently placed at a terminal in over 90% of instances. For example, $n25$ is optimally placed at NIT for 98% of the 2000 iterations. When a berth schedule is made, these vessels can be allocated to their respective terminal with confidence. The remaining 16 vessels are less robust in their allocations and need further attention. For instance, $n1$ is placed at NIT 41% of iterations, 58% at VIG, and 1% at PMT. That means that there exist combinations of possible input variables where the berth schedule that minimizes cost has vessel $n1$ at each of the three terminals. Rarely, the solution places the vessel at PMT, but the distribution among NIT and VIG does not give a strong indication for where it should be placed for optimal operations.

Table 4-9. Vessel allocation to terminals for stochastic inputs. The most common terminal for each vessel is bolded. The result of the deterministic scheduling is included for reference.

	NIT	VIG	PMT	*Deterministic allocation*
n1	41%	**58%**	1%	*NIT*
n2	22%	**78%**	0%	*VIG*
n3	47%	**53%**	0%	*NIT*
n4	**100%**	0%	0%	*NIT*
n5	28%	**72%**	0%	*VIG*
n6	**86%**	13%	0%	*NIT*
n7	**100%**	0%	0%	*NIT*
n8	**100%**	0%	0%	*NIT*
n9	**85%**	15%	0%	*NIT*
n10	**93%**	7%	0%	*NIT*
n11	0%	**100%**	0%	*VIG*
n12	36%	**64%**	0%	*NIT*
n13	7%	**93%**	0%	*VIG*
n14	**58%**	42%	0%	*VIG*
n15	21%	**79%**	0%	*VIG*
n16	2%	**98%**	0%	*VIG*
n17	18%	**82%**	0%	*NIT*
n18	30%	**70%**	0%	*NIT*
n19	**96%**	4%	0%	*NIT*
n20	**97%**	3%	0%	*NIT*
n21	29%	**71%**	0%	*VIG*
n22	12%	**88%**	0%	*VIG*
n23	**59%**	41%	0%	*VIG*
n24	**65%**	35%	0%	*VIG*
n25	**98%**	2%	0%	*NIT*
n26	0%	**100%**	0%	*VIG*
n27	**95%**	5%	0%	*NIT*
n28	**52%**	48%	0%	*NIT*
n29	**99%**	1%	0%	*NIT*
n30	4%	**96%**	0%	*VIG*
n31	**93%**	7%	0%	*NIT*

Figure 4-13 to Figure 4-18 show histograms of system performance measures. Table 4-9 to Table 4-14 show summary statistics for the same measures: mean, minimum, and maximum. For system cost (Figure 4-13 and Table 4-9), the values range between \$2.77 million and \$3.63 million with a mean of \$3.20 million, which mean the minimum and maximum swing approximately 13% from the mean. When comparing this to the cost per container (Figure 4-14 and Table 4-10), the swing from the mean there is smaller, about 3% from the mean of \$101 per container to a \$98 minimum and \$104 maximum. The larger swing in the total system cost is explained by the variations in the number of containers handled, which is one of the stochastic variables.

System delay is illustrated in Figure 4-15 and Table 4-11. The range of values is between 80 hours and 248 hours with a mean of 160 hours. This large gap can be partially explained by no penalty being placed on longer delays, except the 12 hour constraint for each vessel. This means that there is no preference given to solutions that have shorter delays. In future work, this should be a topic of importance.

Berth utilization varies significantly be terminal. The mean goes from over 80% at VIG (Figure 4-17 and Table 4-13) to 40% at NIT (Figure 4-16 and Table 4-12) to almost 0% at PMT (Figure 4-18 and Table 4-14). NIT and VIG both have close to symmetrical histograms. At PMT, on the other hand, most iteration have a utilization under 1% which mean no or one vessel scheduled at the terminal.

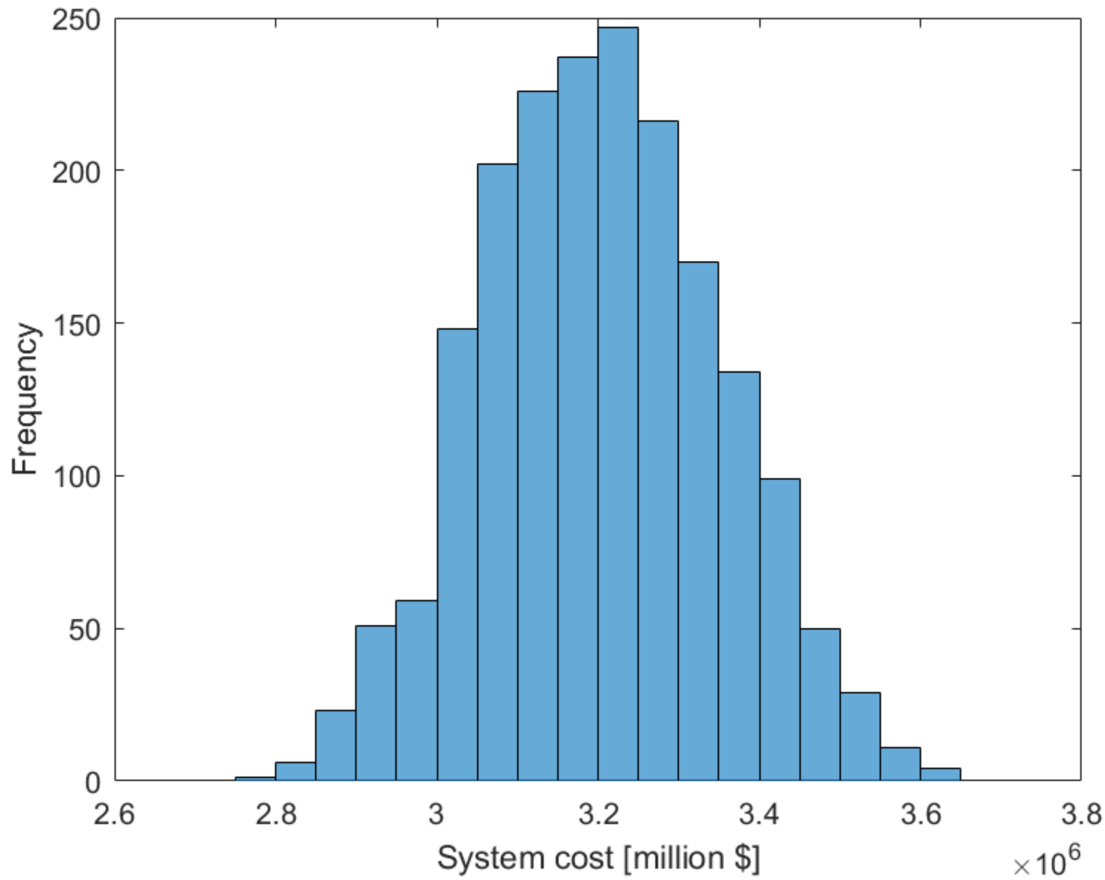

Figure 4-13. System cost distribution for berth scheduling.

Table 4-10. Summary statistics for system cost for berth scheduling.

	System cost
Mean	\$3.20 million
Minimum	\$2.77 million
Maximum	\$3.63 million

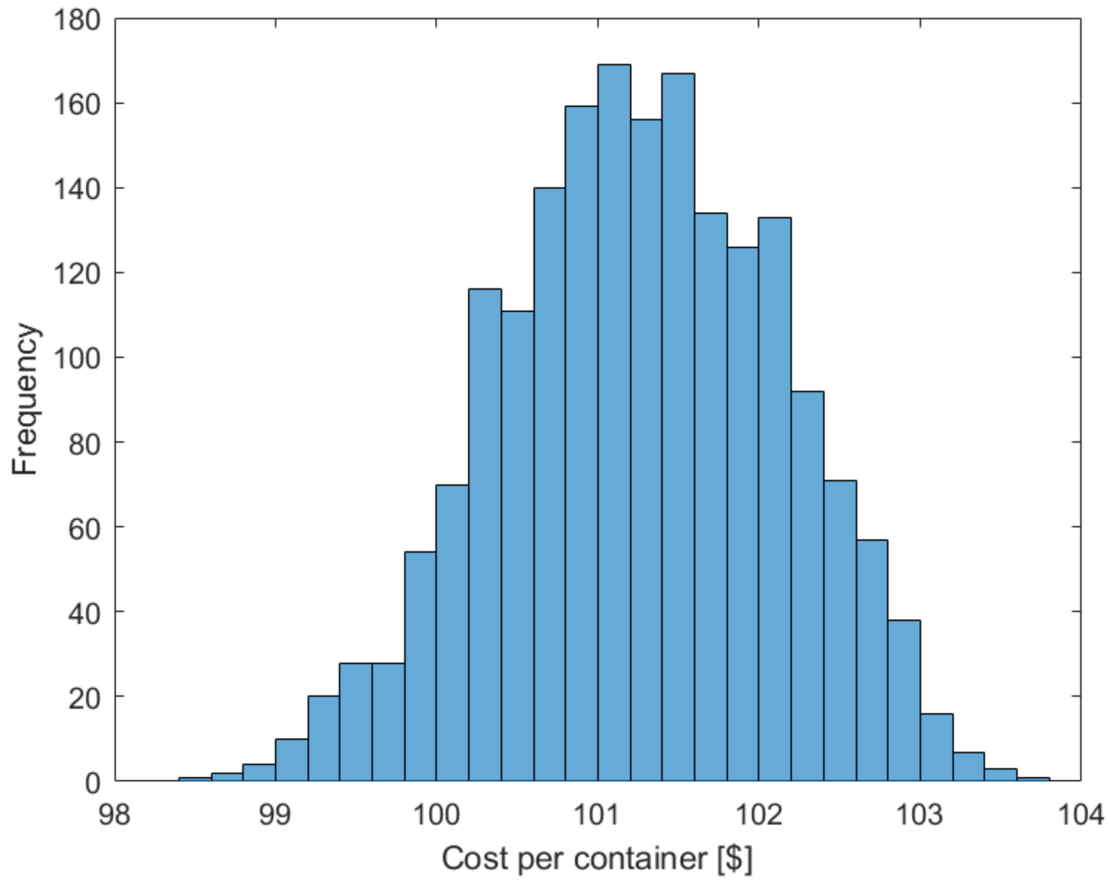

Figure 4-14. Cost per container for berth scheduling.

Table 4-11. Summary statistics for cost per container for berth scheduling.

	Cost per container
Mean	$101
Minimum	$98
Maximum	$104

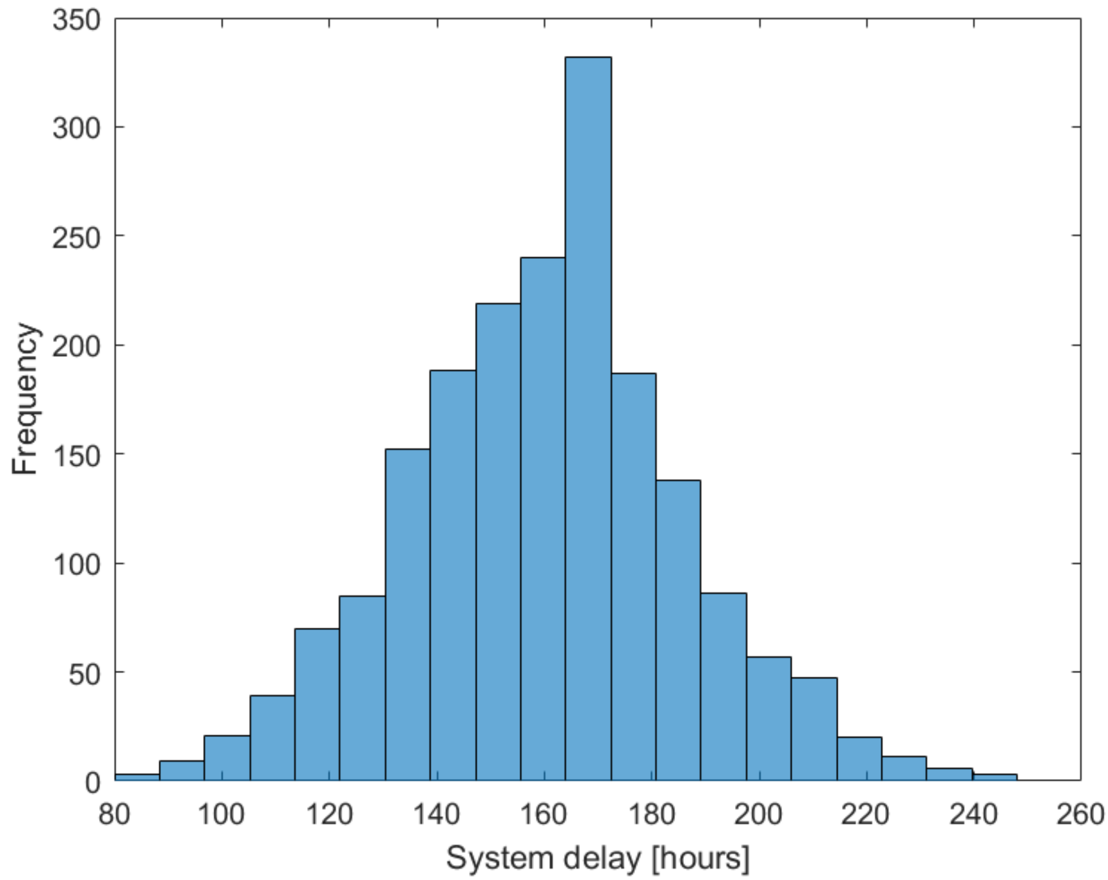

Figure 4-15. System delays for berth scheduling.

Table 4-12. System delay for berth scheduling.

	System delays
Mean	160 hours
Minimum	80 hours
Maximum	248 hours

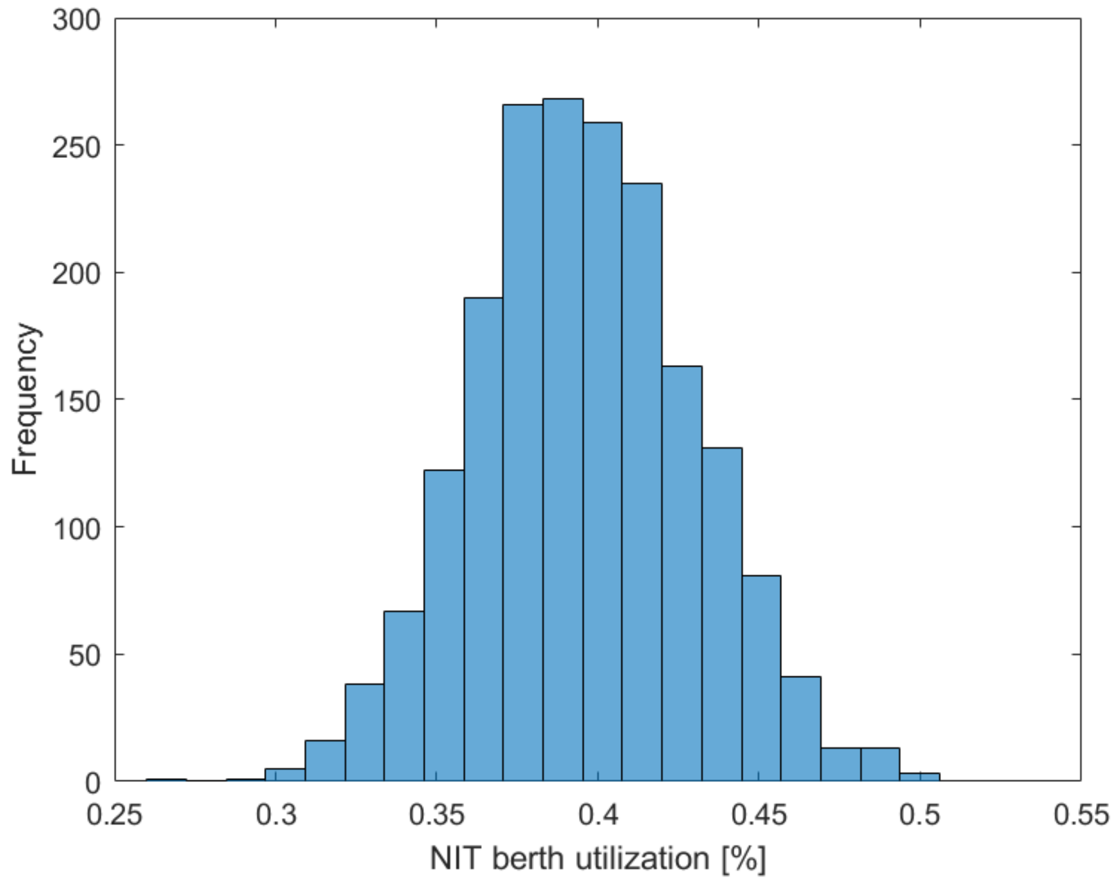

Figure 4-16. Berth utilization at NIT.

Table 4-13. Summary statistics on berth utilization at NIT.

	NIT berth utilization
Mean	40%
Minimum	26%
Maximum	51%

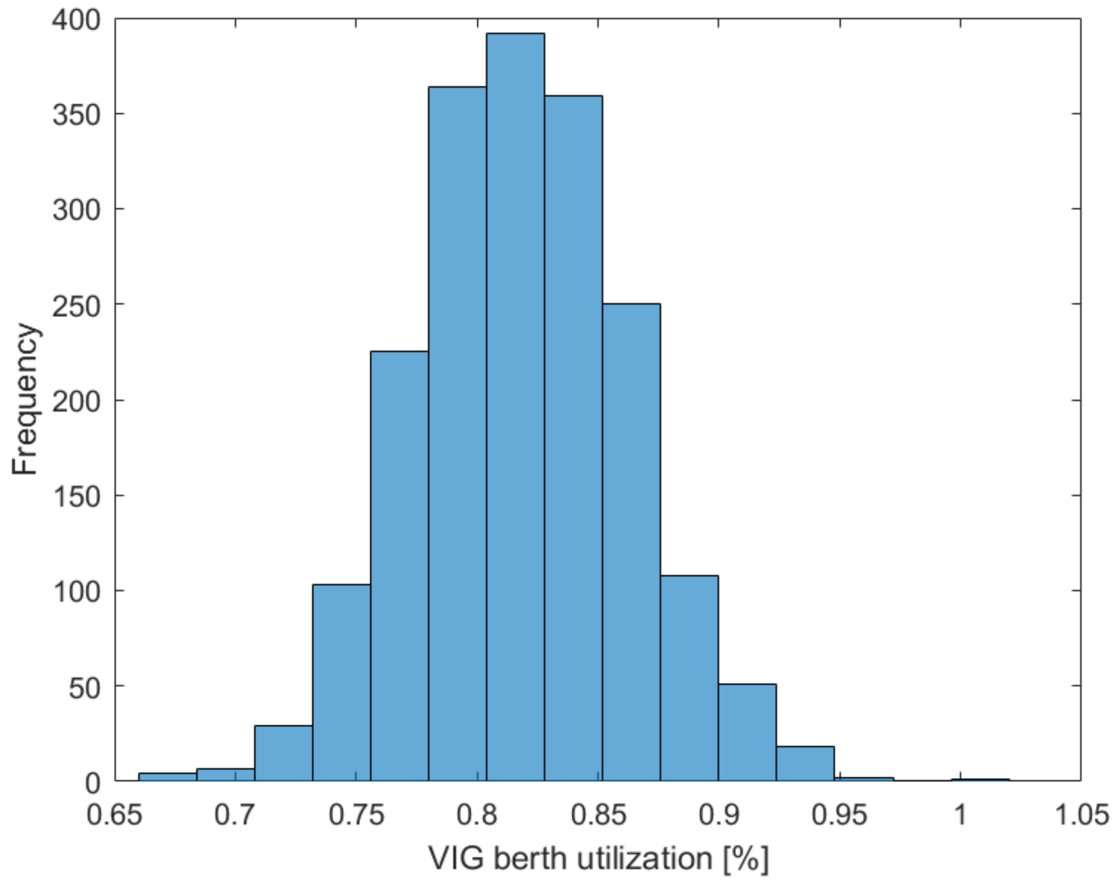

Figure 4-17. Berth utilization at VIG.

Table 4-14. Summary statistics on berth utilization at VIG.

	VIG berth utilization
Mean	82%
Minimum	67%
Maximum	100%

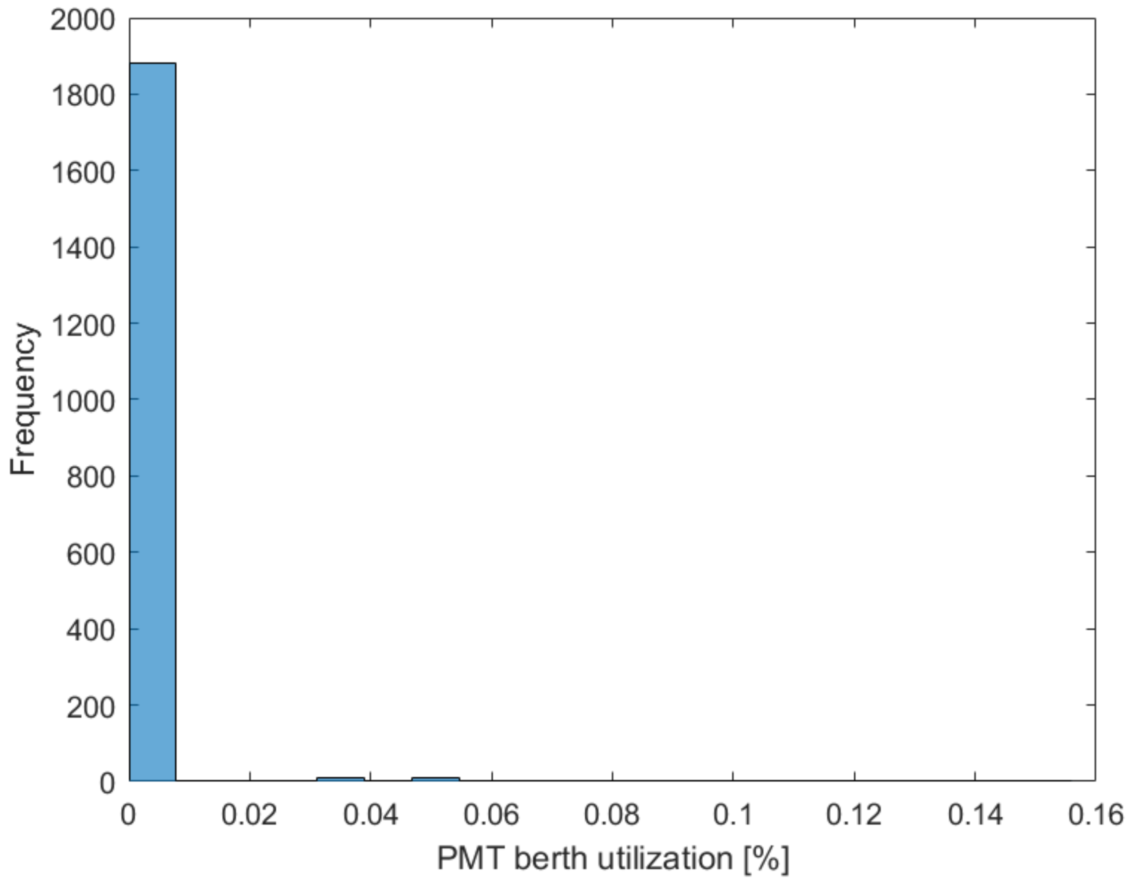

Figure 4-18. Berth utilization at PMT.

Table 4-15. Summary statistics on berth utilization at PMT.

	PMT berth utilization
Mean	0.8%
Minimum	0%
Maximum	15%

The results presented in this section will serve as a baseline for the remainder of the analysis. In the next section, disruptions to the schedule are introduced. This includes limiting terminal capacity and changing the overall system demand (that is number of containers across all vessels). Until now, stochastic variables have been kept within what can be considered normal operating conditions, that is, fluctuations that are not traced to any specific irregular conditions.

Summary

This chapter demonstrates a system analysis for maritime container port operations, with a focus on vessel berth scheduling and applications at the Port of Virginia in Norfolk, VA, USA. It discusses stakeholders, scheduling processes, data availability and needs, and associated uncertainties. It formulates an approach for vessel berth scheduling, assigning a location and time to incoming vessels, taking into account stochasticity in input variables. The approach combines mixed-integer linear programming, Monte Carlo simulation and statistical analysis. Results are presented for an as-planned scenario which will be used as a baseline for the following chapters when alternative scenarios are considered.

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Thorisson, H., C.A. Pennetti, D.J. Andrews, D. Hendrickson, T.L. Polmateer, J.H. Lambert. 2019. Systems Modeling and Optimization of Container Ship Berthing with Various Enterprise Risks. To appear in Proceedings of the 2*019 IEEE Systems Conference*. Orlando, FL, USA. 8pp.

Chapter 5

Demonstration: Disruptions from operational conditions

Overview

This demonstration exercises a schedule of vessel arrivals at a maritime container port with operations disruptions including capacity constraints during construction, varying cargo volumes, and others (Thorisson et al. 2019a). Table 5-1 summarizes the overview.

Table 5-1. Overview of Chapter 5, demonstrating operational disruptions to vessel berth scheduling.

Chapter objective	Quantify sensitivity of vessel berth scheduling to disruptions of operations factors
Motivation	External and internal operational factors often arise and schedules need to be robust
Approach and data	36 disruptions of different combinations of terminal capacity constraints and volume adjustments
Contributions	Demonstration of methodology of vessel berth scheduling Demonstration of disruption coefficient quantification

Background

Schedules need to be resilient, not only to small, frequent variations, but also to larger longer-term evolutions or sudden shocks. In the context of port operations, these larger disruptions can affect several of the components in the optimization model: arrival and handling times, the number of containers handled terminal capacity, the number of available berths, and others. Scenario analysis (Godet, 2000) can be useful to envision the various emergent and future conditions that can affect operations schedules. In the demonstration, a number of scenarios are created and evaluated. Each scenario has a unique combination of selected key model components. The schedule outputs from the different scenarios are then compared and contrasted.

Kullback-Leibler divergence was first introduced as a measure of directed divergence or similarity between two random variables (Kullback & Leibler, 1951). An important measure in information theory, it can be interpreted as the information gained by using one probability distribution instead of another (Alaa & Schaar, 2018; Sankaran, Sunoj, & Nair, 2016). Examples of recent use in engineering systems modeling is to estimate how much information is gained by additional parameters for seismic intensity measures (Dhulipala, Rodriguez-Marek, & Flint, 2018) and the optimization of experimental design (Walsh, Wildey, & Jakeman, 2018). In this chapter is used to quantify the departure of a disrupted schedule assignment from a baseline assignment.

Technical approach

The scheduling approach described in Chapter 4 is modified to simulate the effects of various operational disruptions. The disruptions analyzed in this chapter are combinations of various terminal capacities and container numbers handled (demand for service). In the optimization model, the terminal capacities are modeled are the parameter MAX_p in the constraint $(viii)$:

$$\sum_{n=1}^{N}\left(x_{np}\sum_{m=1}^{M} TEU_{nm}\right) \leq MAX_p \tag{5-1}$$

Changing this parameter allow more/less containers to be handled at a particular terminal during the optimization time frame.

Changing the container volume handled is modeled through the cost vector, c_{np}^T, in the objective function of the optimization model:

$$\min_{n,p} c_{np}^T x_{np} \tag{5-2}$$

The cost vector is in turn the product of the containers to be handled by each of the three modes and the unit cost of unloading a container by mode by terminal:

$$c_{np} = TEU_{nm} \times g_{pm}{}' \tag{5-3}$$

In this part of the demonstration, the total volumes are modified to simulate more containers on each vessel but the same number of vessels. This is done by adding a multiplier, $\alpha > 0$, so the cost vector is:

$$c_{np} = \alpha\, TEU_{nm} \times g_{pm}{}' \tag{5-4}$$

As described in the data section, disruptions with different terminal capacities and volume multipliers are generated and Monte Carlo simulation varying arrival times, handling times, and container volumes by vessel is run. As in the previous chapter, system cost, cost per container, system delays, and terminal berth utilization is observed for each disruption. Disruption measures, described in Chapter 3, quantify the disruption to each performance measure in the disruptions.

Kullback-Leibler divergence or information gain (Joyce, 2011; Kullback & Leibler, 1951; Sankaran et al., 2016) moving from a prior distribution $g(x)$ to a posterior $f(x)$ is defined for continuous random variables as:

$$D_{KL}(f,g) = \int_{-\infty}^{\infty} f(x) \ln\left(\frac{f(x)}{g(x)}\right) dx \tag{6-3}$$

For discrete random variables defined over set $\mathcal{X}$, the definition is:

$$D_{KL}(f,g) = \sum_{x \in \mathcal{X}} f(x) ln\left(\frac{f(x)}{g(x)}\right) \tag{6-4}$$

Kullback-Leibler divergence is not a proper metric, but it satisfies the properties of nonnegativity and identity of indiscernibles:

- $D_{KL}(f,g) \geq 0$
- $D_{KL}(f,g) = 0 \Leftrightarrow f = g$

The metric will be used in this chapter to quantify the departure of the schedule assignments, $f(x)$ of vessels from a baseline case, $g(x)$.

Data

Ports, similar to other industries, operate in an environment constantly evolving. There is seasonality in imports and exports, facilities have to be updated on a regular basis, and other conditions in the supply chain, upstream and downstream from the port, that can disrupt terminal operations. In this section, three variables are selected for a sensitivity analysis: overall container volume (number of containers on all vessels), NIT capacity, and VIG capacity. Table 5-1 describes the disruptions selected for analysis. They consist of combinations of the three variables. For two variables, VIG capacity and total container volume, three values are included: an expected value, a low, and a high estimate. For NIT capacity, four values are included: an expected value, two different low values, and a high value. The values are not considered to have one specific cause, but rather can be the result of multiple different causes. For example, construction might limit terminal capacity by clocking of parts of the facilities or taking up resources; the same capacity limitation might be the result of a natural disaster that temporarily cause resources to be out of service. Specific disruption can then be derived be a particular combination of the variables. Conversely, a highly disruptive combination that has not been considered by operators before might lead to new discussions and knowledge discovery.

Table 5-2. Model parameter for 36 disruptions of vessel berth scheduling. Note there is no Disruption 19 as this would be identical to case 0.

Disruption	NIT capacity	VIG capacity	Total volume multiplier
0	***20000***	***17500***	***1***
1	10000	10000	0.75
2	15000	10000	0.75
3	20000	10000	0.75
4	25000	10000	0.75
5	10000	17500	0.75
6	15000	17500	0.75
7	20000	17500	0.75
8	25000	17500	0.75
9	10000	22500	0.75
10	15000	22500	0.75
11	20000	22500	0.75
12	25000	22500	0.75
13	10000	10000	1
14	15000	10000	1
15	20000	10000	1
16	25000	10000	1
17	10000	17500	1
18	15000	17500	1
20	25000	17500	1
21	10000	22500	1
22	15000	22500	1
23	20000	22500	1
24	25000	22500	1
25	10000	10000	1.25
26	15000	10000	1.25
27	20000	10000	1.25
28	25000	10000	1.25
29	10000	17500	1.25
30	15000	17500	1.25
31	20000	17500	1.25
32	25000	17500	1.25
33	10000	22500	1.25
34	15000	22500	1.25
35	20000	22500	1.25
36	25000	22500	1.25

Results

As a motivating example, disruption 17 (s17) is studied in further detail. Figure 5-1 to Figure 5-6 illustrate empirical probability distributions of performance measures for two scenarios, the baseline or business-as-usual scenario (s0) and the disruption where NIT capacity is lowered from 20,000 to 10,000 containers per week while VIG capacity and total container volume are at baseline levels (s17). Table 5-2 summarizes the disruption coefficients from the six performance measures.

The system cost is illustrated in Figure 5-1. For s17, the mean of the distribution in higher than for s0. The two distributions have a similar shape, yet for s17 the peak of the distribution is lower. About 24% of the area under each curve is not shared with the other. The cost per container (Figure 5-2) is disrupted more by the limited NIT capacity and 75% of the area under the curve is not shared among the two scenarios. The disrupted curve is wider and has a lower peak than the baseline. The mean is shifted from $101 to $104.

The system delay distributions (Figure 5-3) are more similar between the baseline and the disrupted scenario. There is a 5% disruption, based on the lack of overlap. The shape and height of the distributions is not significantly changed.

The terminal utilizations are the most heavily disrupted performance measures, especially for NIT and PMT. The disruption of area under the curve for NIT (Figure 5-4) is 98% and the mean goes down from 40% to about 27%. The disrupted distribution is also narrower and taller. VIG (Figure 5-5) is less disrupted than the other two terminals, or 25%. It is shifted slightly to the left, meaning a lower mean. PMT (Figure 5-6) which close to unutilized in the baseline scenario is 99% disrupted, with the mean going up to about 30%.

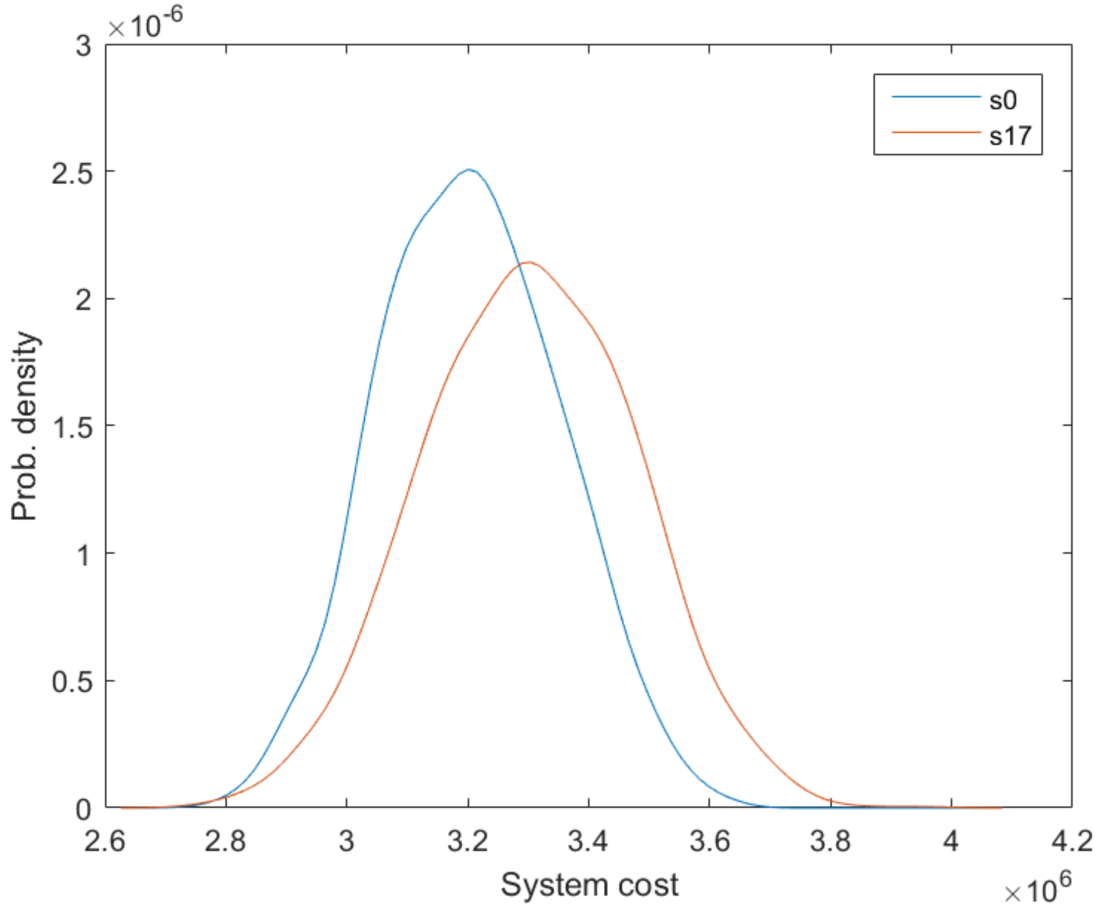

Figure 5-1. Disrupted system cost distribution when NIT capacity is lowered from 20,000 to 10,000 containers per week. The disruption coefficient is D=0.24.

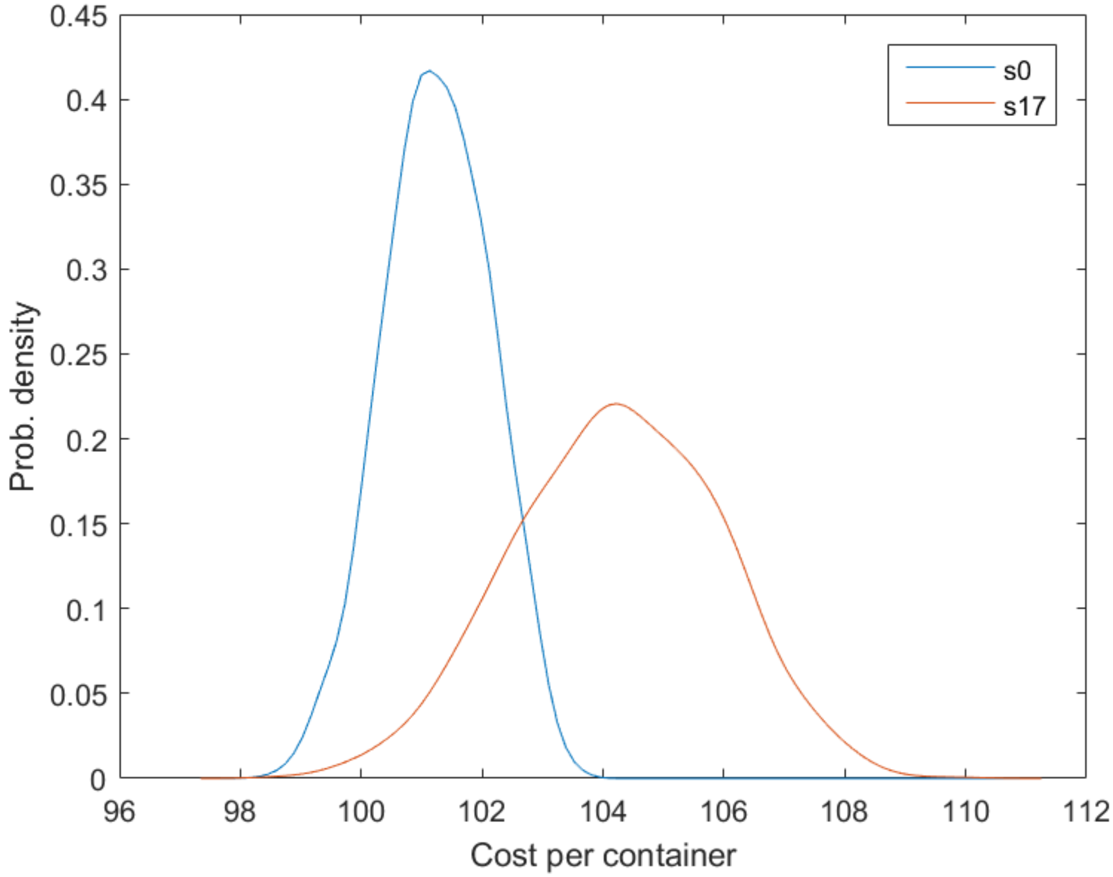

Figure 5-2. Disrupted cost per container distribution when NIT capacity is lowered from 20,000 to 10,000 containers per week. The disruption coefficient is D=0.75.

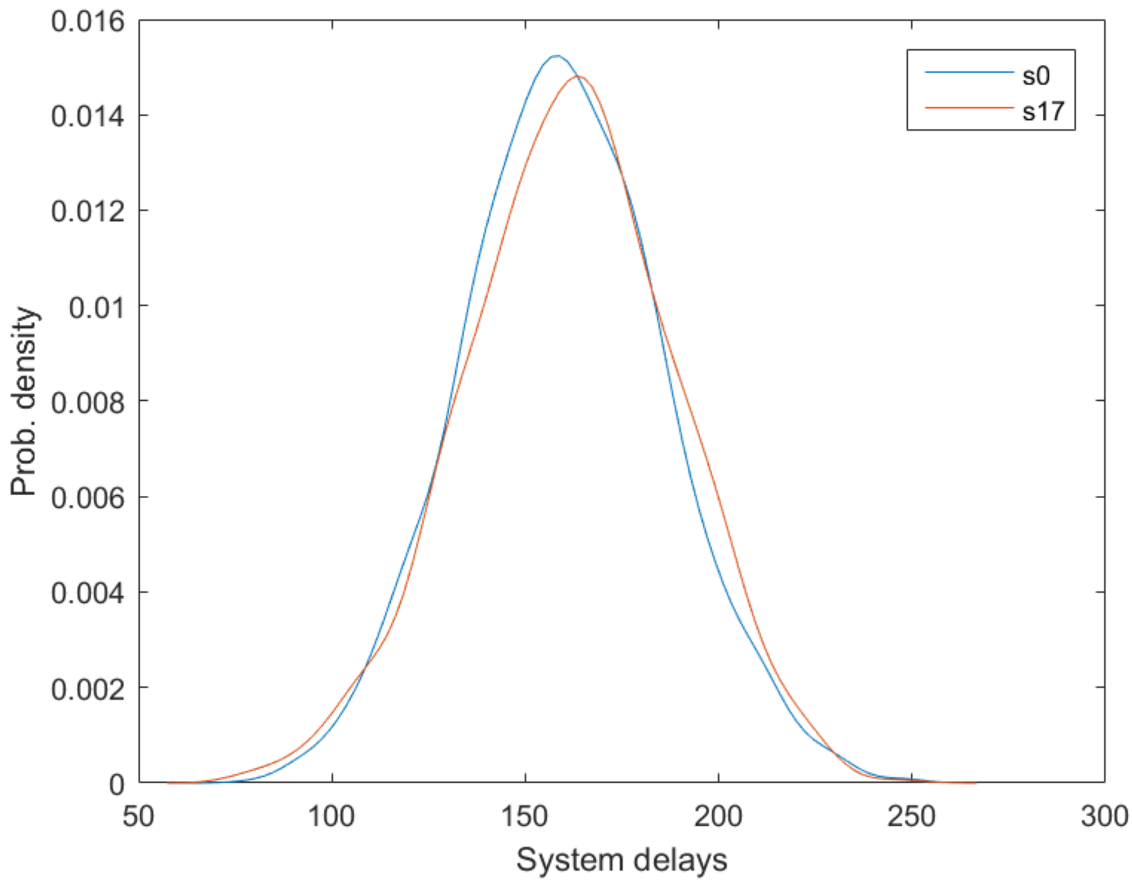

Figure 5-3.Disrupted system delays distribution when NIT capacity is lowered from 20,000 to 10,000 containers per week. The disruption coefficient is D=0.05.

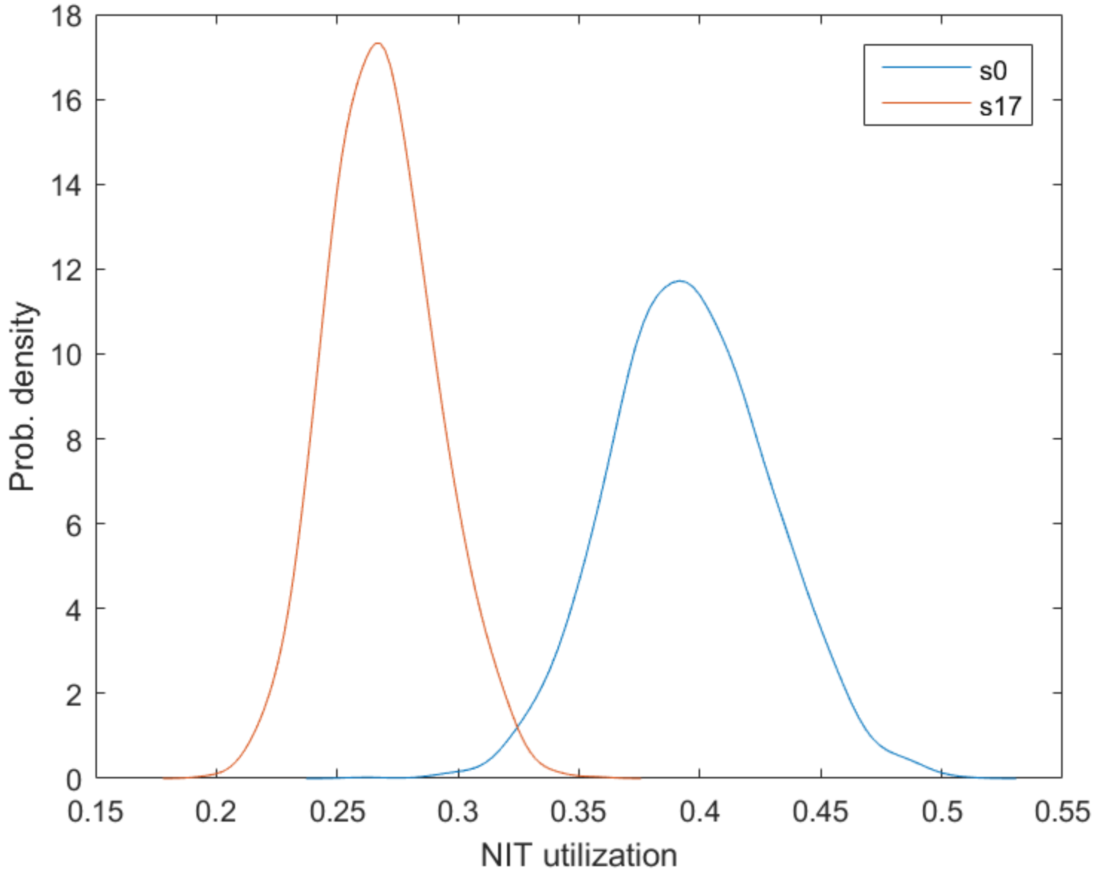

Figure 5-4. Disrupted NIT utilization distribution when NIT capacity is lowered from 20,000 to 10,000 containers per week. The disruption coefficient is D=0.98.

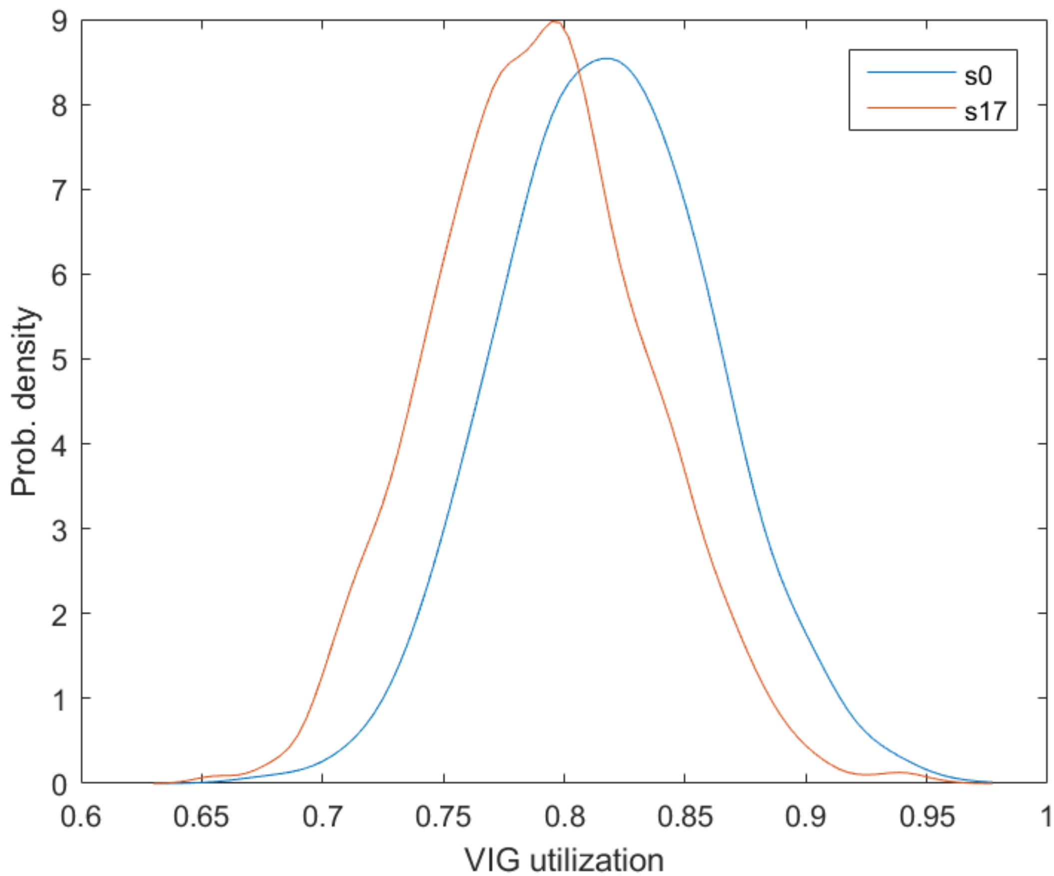

Figure 5-5. Disrupted VIG utilization distribution when NIT capacity is lowered from 20,000 to 10,000 containers per week. The disruption coefficient is D=0.25.

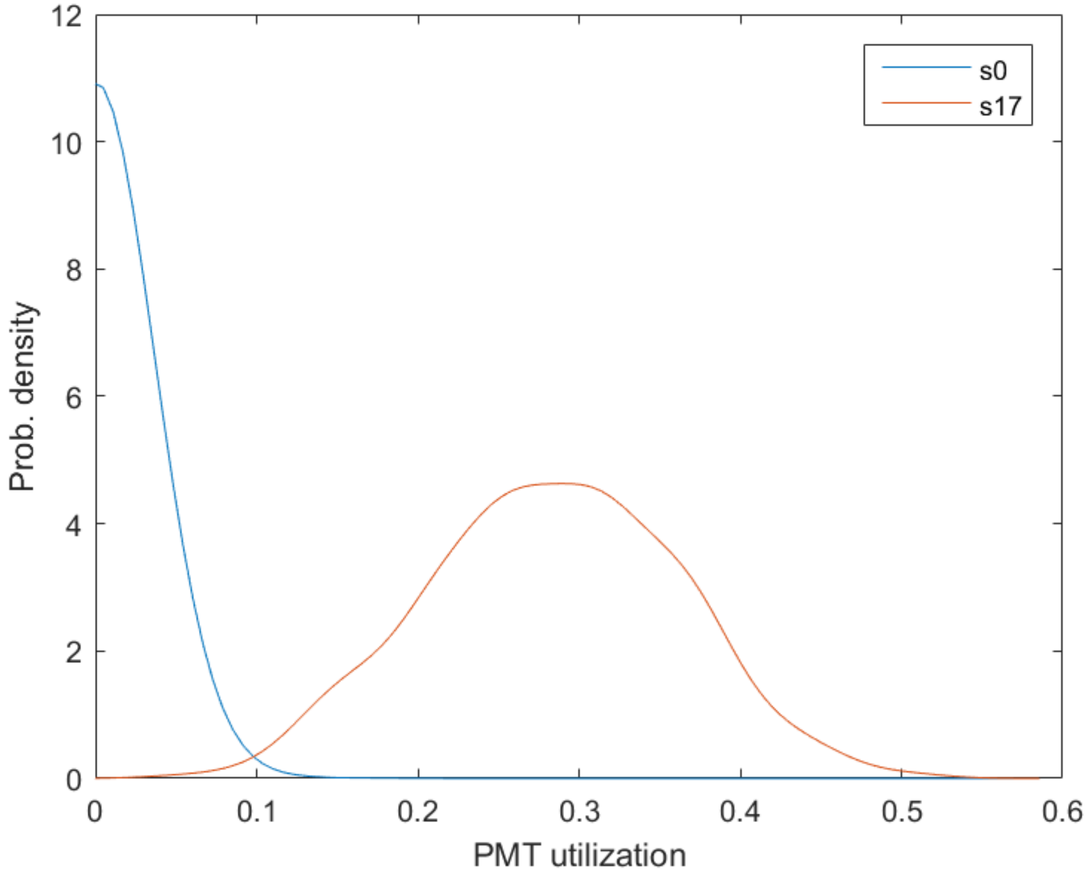

Figure 5-6. Disrupted PMT utilization distribution when NIT capacity is lowered from 20,000 to 10,000 containers per week. The disruption coefficient is D=0.99.

Table 5-3. Disruption coefficients of performance measures for s17, when NIT capacity is lowered from 20,000 to 10,000 containers per week.

Performance measure	Disruption coefficient
System cost	0.24
Cost per container	0.75
System delays	0.05
NIT utilization	0.98
VIG utilization	0.25
PMT utilization	0.99

Table 5-3 to Table 5-8 show the disruption coefficients for the six performance measures, for each of the 36 disruptions. The disruption coefficient for the system cost (Table 5-3) is highly correlated with cargo volume, as all disruptions with $\pm 25\%$ of container numbers have a disruption coefficient of 0.95 or greater. For the disruptions with 25% reduction in volume, the disruption coefficient is less than one when VIG capacity is low (10,000 containers per week). Symmetrically, when volume is increased by 25%, the disruption coefficient is less than one for high VIG capacity (22,500 containers per week). For the disruptions when volume is at baseline level, VIG capacity is more influential to the disruption coefficient than NIT capacity.

Table 5-4 shows the disruption coefficients for the cost per container. The disruption coefficient is 1 for all disruptions where the volume is 25% reduced and when VIG capacity is 10,000 containers per week. When volume is increased by 25%, increasing the capacity of VIG to 22,500 containers per week reduces the disruption from 1 or 0.99 to 0.31 or less when NIT capacity is at least 15,000 or 0.85 when NIT capacity is 10,000. Increasing NIT capacity to 25,000 does not have the same effect with VIG capacity at 17,500 or 10,000. This indicates that if there is an expected long-term increase in container numbers, priority should be given to expansion of VIG rather than other terminals.

The system delay disruption coefficients, displayed in Table 5-5, are mostly smaller than the ones for system cost and cost per container. The most influential factor is VIG capacity at 22,500. In those disruptions, the disruption reaches 0.31 for reduced volume. The disruption is less pronounced when the volume is increased.

Table 5-4. System cost disruption coefficients for 36 disruptions of terminal capacity and total container volume. Disruption coefficients marked * are not significant at a 0.05 confidence level.

Total vol. multiplier	VIG capacity	NIT capacity			
		10000	15000	20000	25000
0.75	10000	0.95	0.99	0.99	0.99
0.75	17500	1.00	1.00	1.00	1.00
0.75	22500	1.00	1.00	1.00	1.00
1	10000	0.94	0.82	0.67	0.66
1	17500	0.24	0.03*	0.00*	0.04*
1	22500	0.37	0.38	0.41	0.39
1.25	10000	1.00	1.00	1.00	1.00
1.25	17500	1.00	1.00	1.00	1.00
1.25	22500	0.99	0.98	0.98	0.99

Table 5-5. Cost per container disruption coefficients for 36 disruptions of terminal capacity and total container volume. Disruption coefficients marked * are not significant at a 0.05 confidence level.

Total vol. multiplier	VIG capacity	NIT capacity			
		10000	15000	20000	25000
0.75	10000	1.00	1.00	1.00	1.00
0.75	17500	1.00	1.00	1.00	1.00
0.75	22500	1.00	1.00	1.00	1.00
1	10000	1.00	1.00	1.00	1.00
1	17500	0.75	0.07	0.00*	0.04*
1	22500	0.93	0.96	0.97	0.96
1.25	10000	1.00	1.00	1.00	1.00
1.25	17500	1.00	1.00	0.99	0.99
1.25	22500	0.85	0.31	0.18	0.21

Table 5-6. System delay disruption coefficients for 36 disruptions of terminal capacity and total container volume. Disruption coefficients marked * are not significant at a 0.05 confidence level.

Total vol. multiplier	VIG capacity	NIT capacity			
		10000	15000	20000	25000
0.75	10000	0.16	0.05*	0.12	0.14
0.75	17500	0.17	0.18	0.17	0.16
0.75	22500	0.30	0.31	0.31	0.29
1	10000	0.04*	0.10	0.06	0.04*
1	17500	0.05*	0.03*	0.00*	0.04*
1	22500	0.25	0.23	0.22	0.24
1.25	10000	0.20	0.07	0.08*	0.07
1.25	17500	0.05	0.07	0.04*	0.10
1.25	22500	0.13	0.13	0.12	0.11

Disruption coefficients for NIT utilization are illustrated in Table 5-6. The greatest values of the coefficient are when the capacity of NIT is limited to 10,000 containers per week. The second high disruption factor is when volume is reduced by 25% and VIG capacity is 17,500 or 22,500. Surprisingly, when volume is reduced, VIG capacity is 10,000 and NIT capacity is at least 15,000, the disruption coefficient is low (~0.1). An explanation for this is that in these disruptions, the lower VIG capacity is countered by the lower number of containers. NIT utilization is therefore not as disrupted. A similar effect, but lesser, can be observed when volume is increased by 25% and VIG capacity is at 22,500.

Similarly to NIT, utilization at VIG has the highest disruption coefficients when VIG capacity is at 10,000 containers per week. Table 5-7 demonstrates the disruption coefficients across disruptions. Looking at the relationship between NIT capacity and VIG utilization disruption, there is not a similar correlation as was found between VIG capacity and NIT utilization disruption.

PMT utilization disruption is illustrated in Table 5-8. An interesting pattern in the disruption coefficients is seen when segmenting the table by total volume and looking at the top left corners. First, when volume is reduced by 25%, the combination of 10,000 weekly capacity at both NIT and VIG results in a disruption coefficient of 1 for PMT utilization. Second, when volume is at base level, the combinations resulting in a PMT disruption of 1 are 10,000 at NIT and VIG, 10.000 at NIT and 17,500 at VIG, and 15,000 at NIT and 10,000 at VIG. In other words, these are the disruptions is the upper left corner of the section of the table with base volume. Third, when volume is increased by 25%, the combinations resulting in a disruption coefficient of 1 are in the top left corner but with another diagonal added. Combined, these observations indicate at correlation between disruption coefficient for PMT utilization and the combined capacity of NIT and VIG relative to total volume.

Table 5-7. NIT utilization disruption coefficients for 36 disruptions of terminal capacity and total container volume. Disruption coefficients marked * are not significant at a 0.05 confidence level.

Total vol. multiplier	VIG capacity	NIT capacity			
		10000	15000	20000	25000
0.75	10000	0.93	0.12	0.11	0.12
0.75	17500	0.98	0.98	0.98	0.98
0.75	22500	0.98	0.99	0.99	0.99
1	10000	0.99	0.42	0.91	0.97
1	17500	0.98	0.09	0.00*	0.04*
1	22500	0.87	0.75	0.76	0.75
1.25	10000	1.00	0.77	0.59	0.99
1.25	17500	0.99	0.54	0.82	0.95
1.25	22500	0.99	0.26	0.46	0.48

Table 5-8. VIG utilization disruption coefficients for 36 disruptions of terminal capacity and total container volume. Disruption coefficients marked * are not significant at a 0.05 confidence level.

Total vol. multiplier	VIG capacity	NIT capacity			
		10000	15000	20000	25000
0.75	10000	1.00	0.99	0.99	0.99
0.75	17500	0.55	0.57	0.56	0.55
0.75	22500	0.71	0.74	0.70	0.72
1	10000	1.00	1.00	1.00	1.00
1	17500	0.25	0.03*	0.00*	0.04*
1	22500	0.88	0.87	0.88	0.88
1.25	10000	1.00	1.00	1.00	1.00
1.25	17500	0.75	0.71	0.52	0.33
1.25	22500	0.78	0.83	0.87	0.87

Table 5-9. PMT utilization disruption coefficients for 36 disruptions of terminal capacity and total container volume. Disruption coefficients marked * are not significant at a 0.05 confidence level.

Total vol. multiplier	VIG capacity	NIT capacity			
		10000	15000	20000	25000
0.75	10000	1.00	0.02	0.90*	0.47*
0.75	17500	0.46*	0.55*	0.15*	0.45*
0.75	22500	0.14*	0.44*	0.15*	0.45*
1	10000	1.00	1.00	0.73	0.08*
1	17500	0.99	0.29	0.00*	0.03*
1	22500	0.36	0.01*	0.17*	0.01*
1.25	10000	1.00	1.00	1.00	0.97
1.25	17500	1.00	1.00	0.75	0.08*
1.25	22500	1.00	0.78	0.09*	0.15*

The previous results have focused on the schedule performance, such as cost, delays, and berth utilization. Table 5-10 shows the Kullback-Leibler divergence from the baseline of schedule assignments in the 36 scenarios. The measure is normalized such that the highest disruption is set equal to 1. This quantifies how much the assignments change, e.g. the shift of probabilities of assigning a particular vessel to a particular terminal. The first section of the table, when the volume multiplier is 0.75, has relatively low disruptions. The most disrupted assignments in this section is when both NIT and VIG capacities are lowered to 10,000 containers per week. In the middle section, when the volume is at its baseline level, the combined capacity of VIG and NIT has the highest impact on assignment disruptions. In combinations where the combined capacity of the two terminals is lowered by more than 5,000 containers per week, there is a high disruption of assignments. Conversely, when the combined capacity is higher than in the baseline, the disruptions of assignments are less impactful. In the last section, when volume is multiplied by 1.25, the results are similar but more the disruptions are greater when combined NIT and VIG capacity is lowered.

The results of the disruption of schedule assignments are consistent with what could be expected. A lower capacity at the cheaper terminals, VIG and NIT, moves more vessels towards PMT which has a very low baseline utilization. Similarly, adding capacity at VIG and NIT reinforces their utilization.

Table 5-10. Schedule assignment disruption, quantified using Kullback-Leibler divergence.

Total vol. multiplier	VIG capacity	NIT capacity			
		10000	15000	20000	25000
0.75	10000	0.75	0.06	0.06	0.06
0.75	17500	0.11	0.11	0.12	0.10
0.75	22500	0.10	0.30	0.30	0.30
1	10000	0.98	0.91	0.33	0.12
1	17500	0.64	0.02	0.00	0.00
1	22500	0.20	0.15	0.15	0.15
1.25	10000	1.00	1.00	0.97	0.64
1.25	17500	0.95	0.81	0.26	0.03
1.25	22500	0.82	0.28	0.01	0.01

Summary

This chapter analyzed disruptions of vessel berth scheduling when the system is exposed to various combinations of capacity constraints at the terminals and container volumes (changes in demand). The results demonstrate that the system cost and cost per container are highly disrupted when total volume at the port changes. Increasing the capacity at the VIG terminal has the greatest potential to mitigate disruptions in cost. In terms of capacity constraints, the system is most sensitive to changes in VIG capacity. The third terminal, PMT, has low utilization in the baseline case but becomes important during capacity disruptions at the other two terminals.

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Chapter 6

Demonstration: Disruptions from multiple perspectives

Overview

The previous chapters scheduled vessels by minimizing cost. This chapter considers different objectives, acknowledging the multiple stakeholders of container shipping. The schedule disruptions between various perspectives are evaluated, identifying potential conflicts when schedules are negotiated. Table 6-1 gives an overview of the chapter.

Table 6-1. Overview of Chapter 6, demonstration of multiple perspectives disruptions to vessel berth scheduling.

Chapter objective	Analysis of schedules with different objectives
Motivation	Multiple system stakeholders have different goals that must be balanced in practical situations
Approach and data	Formulate schedules with differing penalties for late berthing of vessels in addition to operational cost
Contributions	Identifying tradeoffs between operational cost, delays, and scheduling information gain

Background

Systems typically have multiple stakeholders and schedules need to balance or at least consider their different priorities in order to operate successfully (Thorisson & Lambert, 2017). Furthermore, priorities can evolve over time and created a need to update schedules and other operations (Thorisson et al. 2017; Whyte et al. 2015). It is therefore necessary that systems engineering includes tools and methods to capture this property. Multiobjective optimization (Chankong & Haimes, 1983) finds non-dominated (Pareto optimal) solutions to optimization problems with multiple objectives. Other approaches combine different objectives by expressing them in a common measure (Xu et al., 2012).

It has been estimated that it costs ocean carriers up to $10,000 per hour a vessel is delayed at a port. It is thus paramount for carriers that delays are minimized. The cost model used in previous chapters is developed for the port operator and takes into account the costs of labor, equipment, capital, overhead, etc. it takes to operate the container port. By including a penalty for late berthing in the optimization objective, the combined operational cost of the port operator and the cost incurred by ocean carriers from delayed schedules is minimized. Comparing the results from several different penalty values can aid in negotiations about what guarantee port operators can give about schedules, or what penalties could be put in place to encourage timely berthing.

In addition to cost of berthing and cost of delaying schedule, a third objective is considered. When vessels are stochastically assigned to terminals, the assignment probabilities give different levels of information about what an optimal placement might be. In other words, assignments can have different levels of stability or robustness to the stochastic conditions that are considered.

Before conducting the optimization and simulation, a vessel can be considered to be equally likely to be each of the three terminals in an optimal solution. After doing the analysis, there might be a higher probability of a particular placement and a lower probability of another. If the probability of a vessel to terminal placement is 1, there is no uncertainty about where the vessels is assigned in an optimal solution, given conditions. This gives rise to quantifying the information gained about the assignments from performing the analysis.

Kullback-Leibler divergence was first introduced as a measure of directed divergence or similarity between two random variables (Kullback & Leibler, 1951). An important measure in information theory, it can be interpreted as the information gained by using one probability distribution instead of another (Alaa & Schaar, 2018; Sankaran, Sunoj, & Nair, 2016). Examples of recent use in engineering systems modeling is to estimate how much information is gained by additional parameters for seismic intensity measures (Dhulipala, Rodriguez-Marek, & Flint, 2018) and the optimization of experimental design (Walsh, Wildey, & Jakeman, 2018).

In vessel scheduling, information gain is measured by moving from an assignment distribution where all assignments are equally likely to an updated one. The mathematics are discussed in the Technical approach section below.

Technical approach

Different perspectives are modeled by changing the objective function of the optimization.

$$\min_{n,p} c_{np}^T x_{np} + d(t_n - a_n) \tag{6-1}$$

Where d is a penalty for berthing a vessel a time period after its arrival. As before c_{np} is the cost of berthing vessel n at terminal p, a_n is the time of arrival and the decision variables are x_{np}

and t_n, designating vessel n is berthed at terminal p and vessel n is berthed at time t_n. In other words, the total cost is both the handling cost, which varies by mode and terminal, and a late berthing penalty. In the baseline case (Chapter 4) and when evaluating operations disruptions (Chapter 5) the penalty for late berthing was zero.

In the original optimization formulation, the constraint $(viii)$ requiring a vessel to be berthed within time δ from arrival:

$$t_n \leq a_n + \delta \tag{6-2}$$

When a penalty is added for late berthing, it may be appropriate to remove this constraint or adjust its parameter.

Kullback-Leibler divergence or information gain (Joyce, 2011; Kullback & Leibler, 1951; Sankaran et al., 2016) moving from a prior distribution $g(x)$ to a posterior $f(x)$ is defined for continuous random variables as:

$$D_{KL}(f, g) = \int_{-\infty}^{\infty} f(x) \ln\left(\frac{f(x)}{g(x)}\right) dx \tag{6-3}$$

For discrete random variables defined over set $\mathcal{X}$, the definition is:

$$D_{KL}(f, g) = \sum_{x \in \mathcal{X}} f(x) ln\left(\frac{f(x)}{g(x)}\right) \tag{6-4}$$

Kullback-Leibler divergence is not a proper metric, but it satisfies the properties of nonnegativity and identity of indiscernibles:

- $D_{KL}(f, g) \geq 0$
- $D_{KL}(f, g) = 0 \Leftrightarrow f = g$

In the special case considered in this chapter, where the prior distribution is that vessels are assigned to one of the three terminals with a 1/3 probability, the information gain for each vessel is defined as

$$D_{KL} = \sum_{j \in \{NIT,VIG,PMT\}} x_{ij} \log_3 \left(\frac{x_{ij}}{1/3}\right) \quad (6\text{-}5)$$

For each vessel i with a posterior probabilities x_{ij}. Changing the base of the logarithm to 3 ensures that the information gain is 1 when $x_{ij} = 1$ for one terminal, j, and $x_{ij} = 0$ for the two other terminals.

Data

This chapter considers six perspectives in addition to the baseline result, and disruptions between are quantified by comparing and contrasting performance measures. The perspectives are summarized in Table 6-1.

Results

This section describes the scheduling results for multiple perspectives. First, there is a detailed exploration of the perspective, s_{inf}, where delays are minimized rather than operational cost. Subsequently, the discussion of results of other perspectives is aggregated with a focus of the disruption of performance measures and the tradeoffs between operational cost, system delays, and terminal assignment information gain.

Table 6-2. Perspectives of operations costs and delay penalties involved in the berth scheduling of vessels at a container port.

Perspective ID	Objective	Details
S_0	Operational cost minimization (baseline)	Port operator main objective
S_1	\$1/hour delay penalty + operational cost	
S_{100}	\$100/hour delay penalty + operational cost	
S_{1000}	\$1,000/hour delay penalty + operational cost	
S_{5000}	\$5,000/hour delay penalty + operational cost	
S_{10000}	\$10,000/hour delay penalty + operational cost	
S_{∞}	Delay minimization	Ocean carrier main objective

S_{inf}: Minimize delays

This section describes the results of vessel berth scheduling when the objective is to minimize delays, rather than operational cost or other objectives. This explores the question of how the port can handle congestion when cost is not a constraint. This could also be viewed as the preferred perspective of ocean carriers, as they are more concerned with keeping the services on schedule than with the operations costs of the ports they call at. The results are presented in the form of terminal assignments, and by analyzing performance measures. Table 6-2 describes the assignments of vessels to terminals for stochastic arrival times, container numbers of handling times. The first vessel, n_1, is required to be at PMT but other vessels can go to any terminal. There are few vessels with consistent assignments to particular terminals, most vessels are spread between all three terminals. This is not surprising as the cost objective is ignored and assignment to a more expensive terminal does not factor in to the objective function.

Table 6-3. Proportions of instances vessels are assigned to terminals when the optimization objective is to minimize delays.

	NIT	VIG	PMT
n1	0.00	0.00	1.00
n2	0.19	0.25	0.55
n3	0.23	0.31	0.47
n4	0.22	0.29	0.49
n5	0.22	0.28	0.50
n6	0.26	0.31	0.43
n7	0.22	0.34	0.43
n8	0.26	0.33	0.41
n9	0.28	0.34	0.38
n10	0.27	0.38	0.35
n11	0.15	0.28	0.57
n12	0.41	0.30	0.29
n13	0.26	0.33	0.42
n14	0.48	0.29	0.23
n15	0.54	0.21	0.24
n16	0.52	0.24	0.24
n17	0.52	0.23	0.25
n18	0.64	0.19	0.18
n19	0.64	0.20	0.16
n20	0.62	0.18	0.20
n21	0.67	0.18	0.16
n22	0.65	0.21	0.14
n23	0.62	0.19	0.19
n24	0.66	0.17	0.16
n25	0.75	0.13	0.11
n26	0.61	0.18	0.20
n27	0.70	0.18	0.12
n28	0.69	0.16	0.15
n29	0.84	0.08	0.08
n30	0.86	0.07	0.07
n31	0.85	0.07	0.07

Figure 6-1 and Table 6-3 illustrate the system cost for the scheduling effort. The cost is significantly higher than in the perspective when cost is minimized. The mean is 4.22 million US$, whereas the mean for cost minimization was 3.20 million. The minimum cost is 3.47 million and the maximum 5.23 million so there is a wide range of cost arising from minimizing delays. The cost per container has a mean of $133 per container and further cost per container illustrations are in Table 6-4 and Figure 6-2.

System delays are minimized in these results. As illustrated in Table 6-5 and Figure 6-3, this objective is met to the fullest in most instances. The maximum system delay is 4 hours (one time period) across the 31 vessels. As illustrated in the histogram, this delay occurs in less than 2% of instances, at other times there is no delay.

Berth utilization (Table 6-6 to Table 6-8 and Figure 6-4 to Figure 6-6) is similar between the three terminals, as the different costs are not taken into account. Each of the three terminals has a mean utilization of 30-40% and a wide range between the minimum and maximum utilization. The terminal that has the fewest berths, VIG, has the largest range of utilization while the terminal with the most berths, NIT, has the smallest.

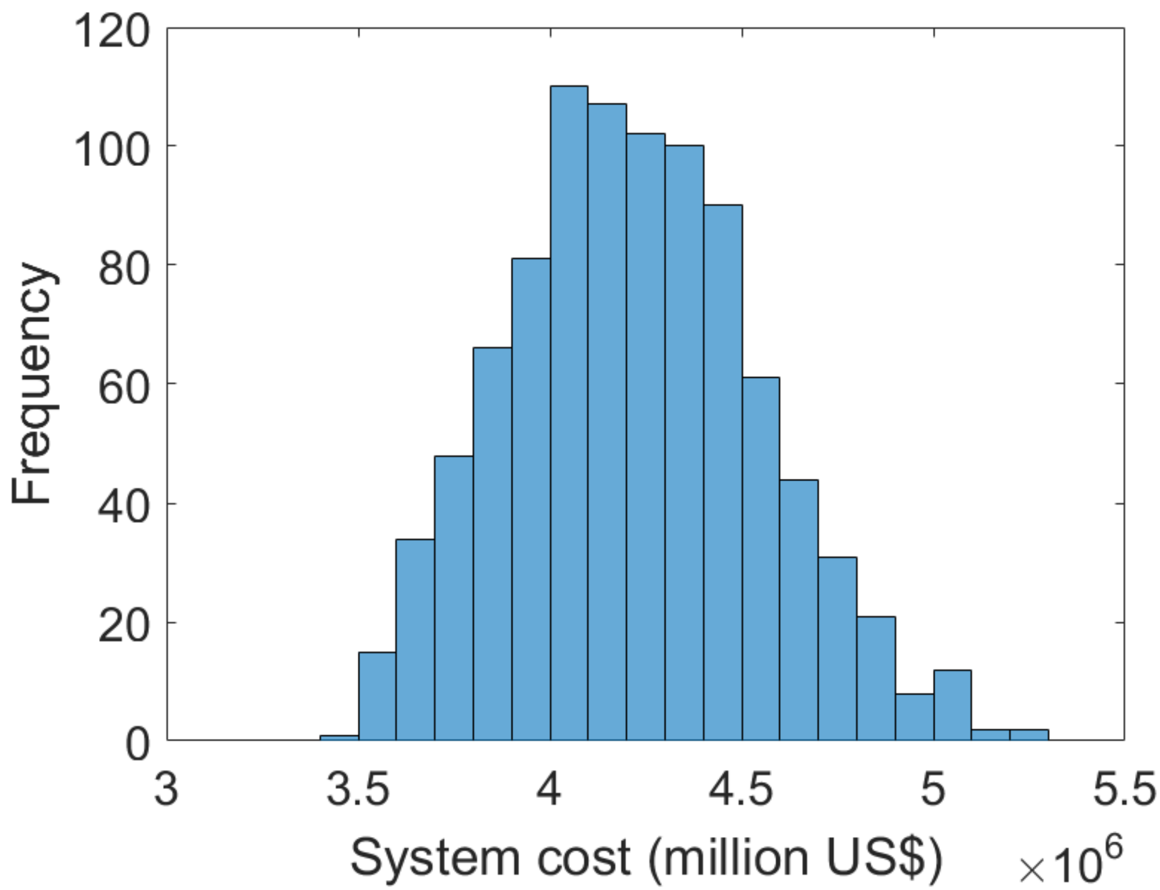

Figure 6-1. System cost distribution for berth scheduling for perspective s_∞.

Table 6-4. Summary statistics for system cost for berth scheduling for perspective s_∞.

	System cost
Mean	$4.22 million
Minimum	$3.47 million
Maximum	$5.23 million

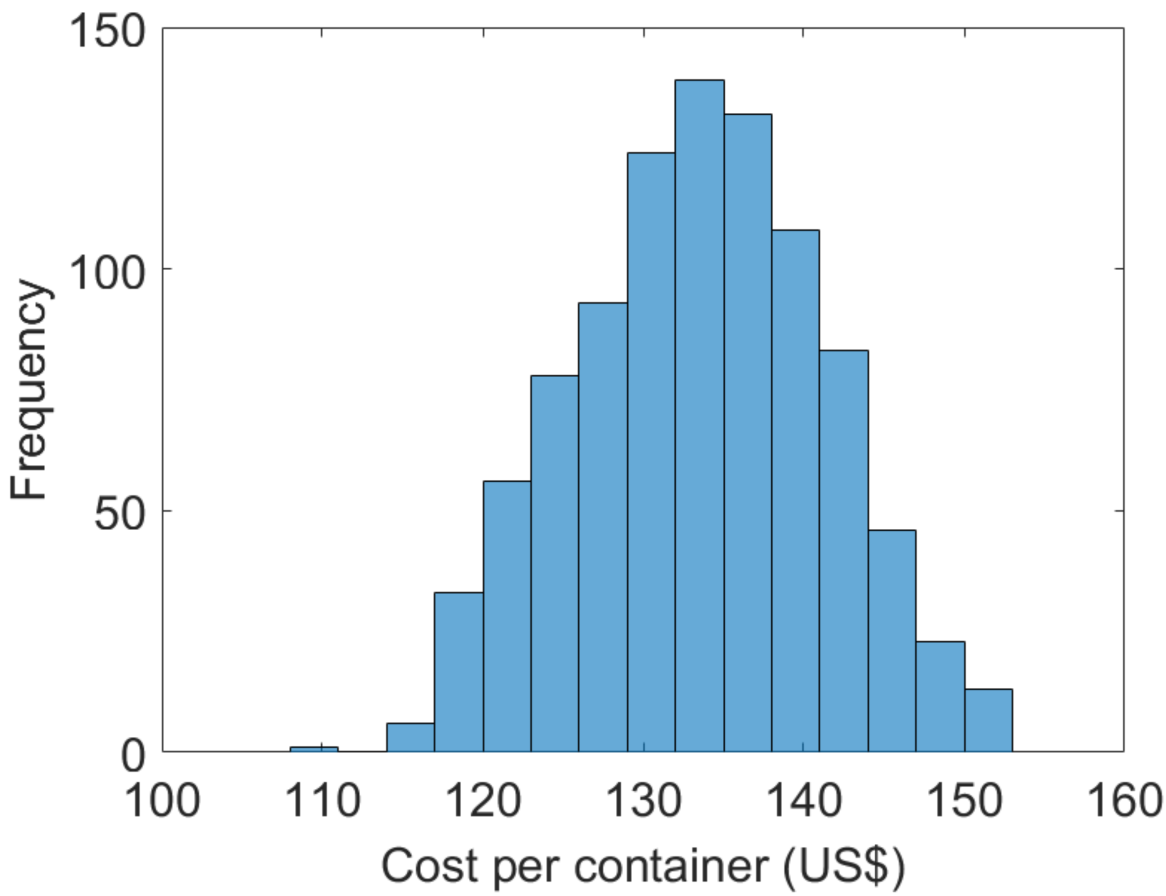

Figure 6-2. Cost per container for berth scheduling for perspective s_∞.

Table 6-5. Summary statistics for cost per container for berth scheduling for perspective s_∞.

	Cost per container
Mean	$133
Minimum	$109
Maximum	$153

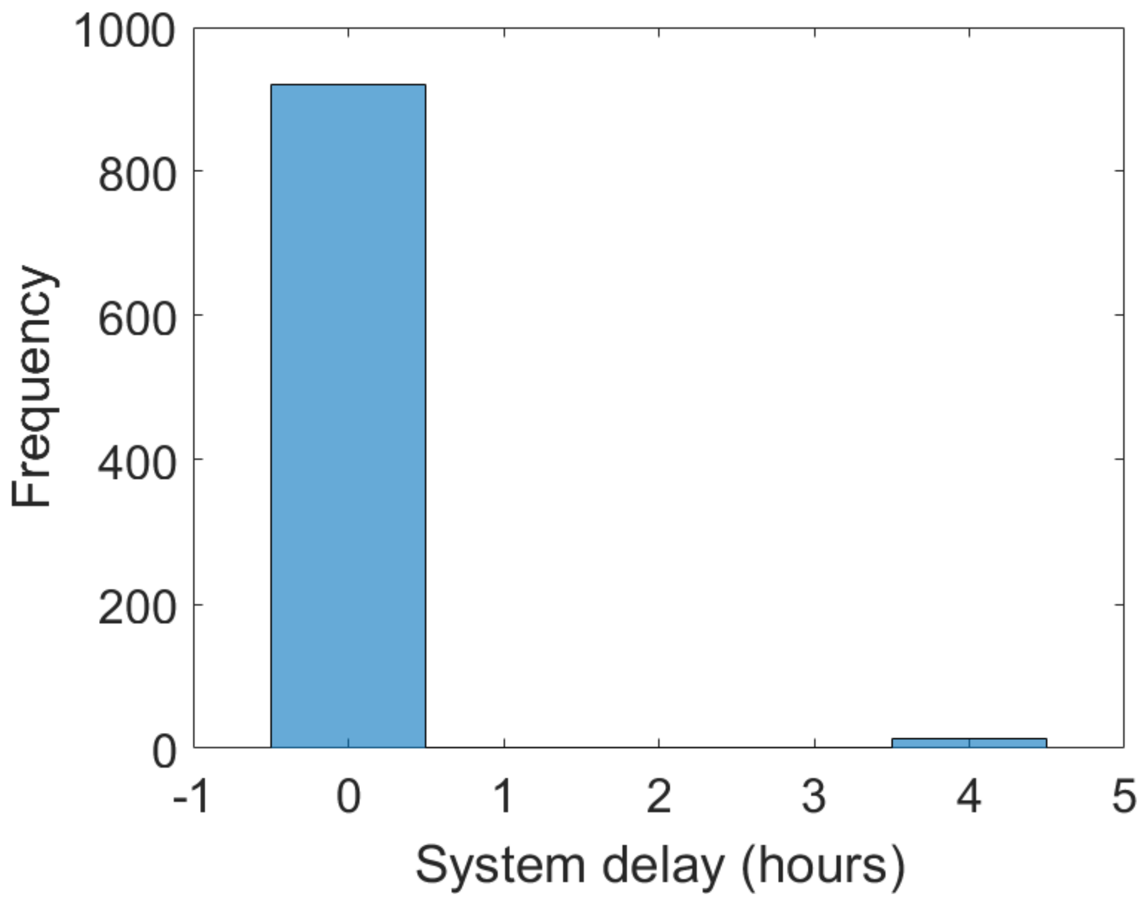

Figure 6-3. System delays for berth scheduling for perspective s_∞.

Table 6-6. System delay for berth scheduling for perspective s_∞.

	System delays
Mean	0.06 hours
Minimum	0 hours
Maximum	4 hours

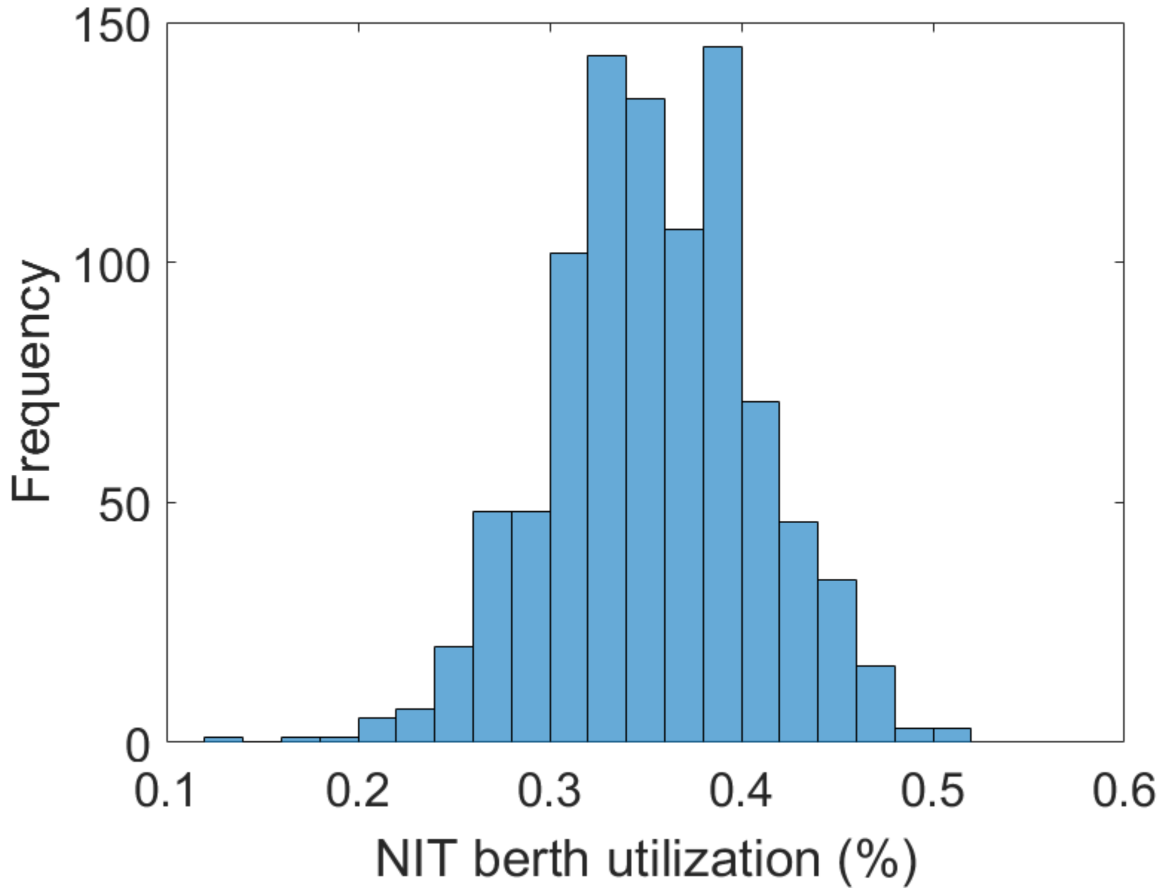

Figure 6-4. Berth utilization at NIT for perspective s_{∞}.

Table 6-7. Summary statistics on berth utilization at NIT for perspective s_{∞}.

	NIT berth utilization
Mean	35%
Minimum	14%
Maximum	51%

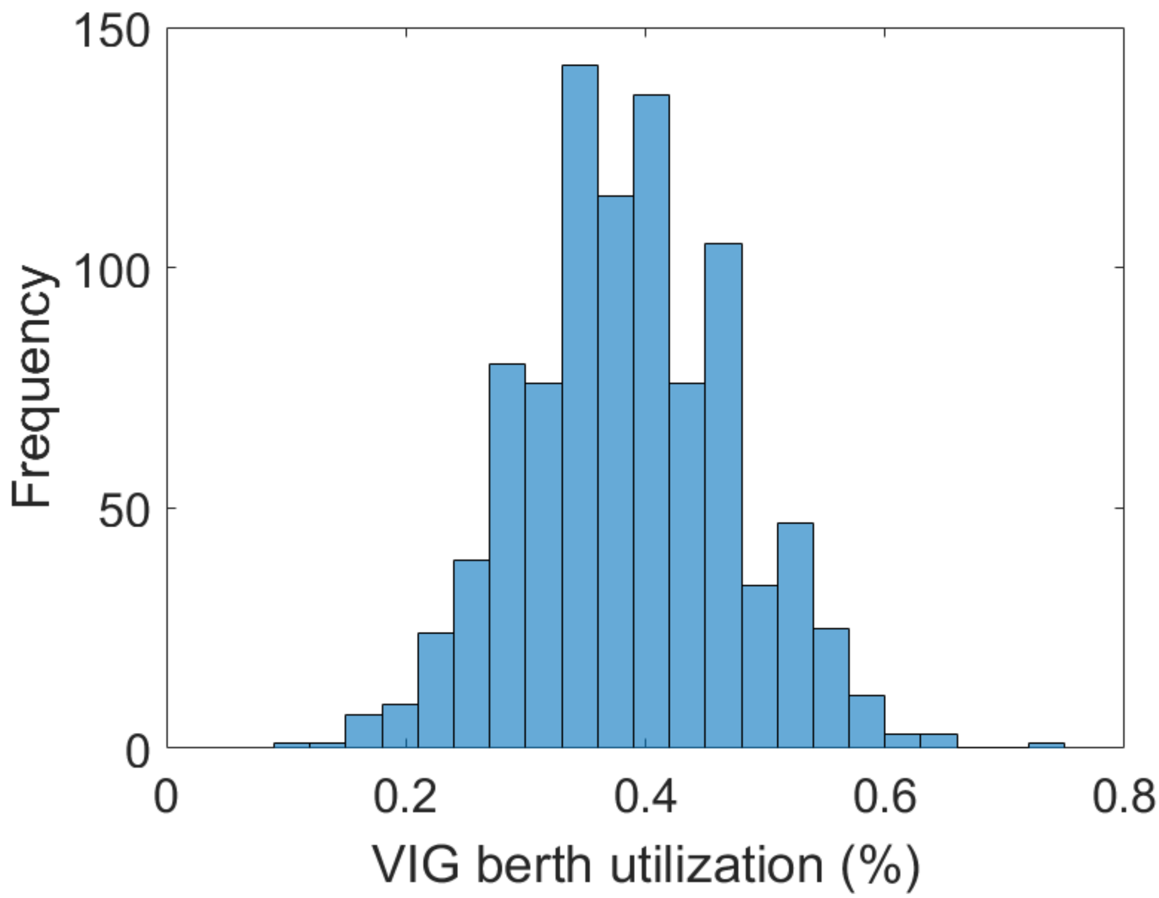

Figure 6-5. Berth utilization at VIG for perspective s_{∞}.

Table 6-8. Summary statistics on berth utilization at VIG for perspective s_{∞}.

	VIG berth utilization
Mean	39%
Minimum	11%
Maximum	74%

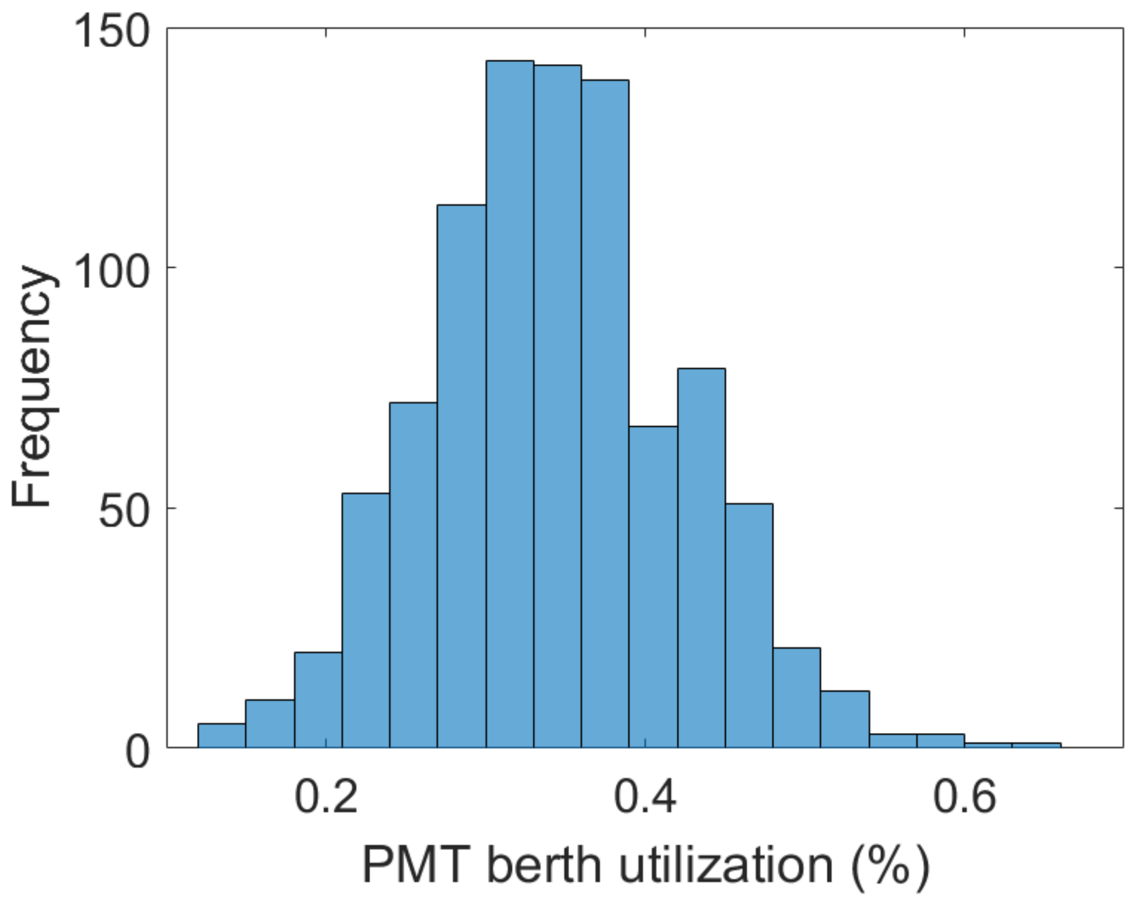

Figure 6-6. Berth utilization at PMT for perspective s_{∞}.

Table 6-9. Summary statistics on berth utilization at PMT for perspective s_{∞}.

	PMT berth utilization
Mean	34%
Minimum	13%
Maximum	66%

Disruptions of perspectives

The system cost is robust for s_0 to s_{10000}, excluding only s_{inf}. In other words, a penalty of up to \$10,000 per hour can be imposed on delays without significant changes to the total berthing cost. This is illustrated in Figure 6-7 and Table 6-9. For each of the disruptions, s_0, s_1, s_{100}, s_{1000}, s_{5000}, s_{10000}, the mean is between 3.24 and 3.29 million USD and the maximum and minimum values of each disruption are similarly within a narrow range. The disruption coefficient of $s_1, s_{100}, s_{1000}, s_{5000}, s_{10000}$ from the baseline s_0 ranges from 0.03 to 0.08, meaning that at most 8% of instances in a disruption fall outside the distribution of the baseline.

As described above, the system cost for s_{inf}, where delays are minimized and operational cost ignored, is significantly disrupted from the cost minimization baseline, s_0.

When the cost is normalized by the number of containers handled, there is again relatively little change between the disruptions where operational cost is included in the objective. The mean ranges between \$102 and \$104 per container and the maximum between \$106 and \$108. The disruption coefficients are greater than those for system cost but under 0.3 for aforementioned disruptions. For s_{inf}, the cost per container is heavily disrupted, with a mean of \$133, maximum of \$153, and the minimum of \$109 is greater than the largest maximum of the other disruptions. This is described in Figure 6-8 and Table 6-10.

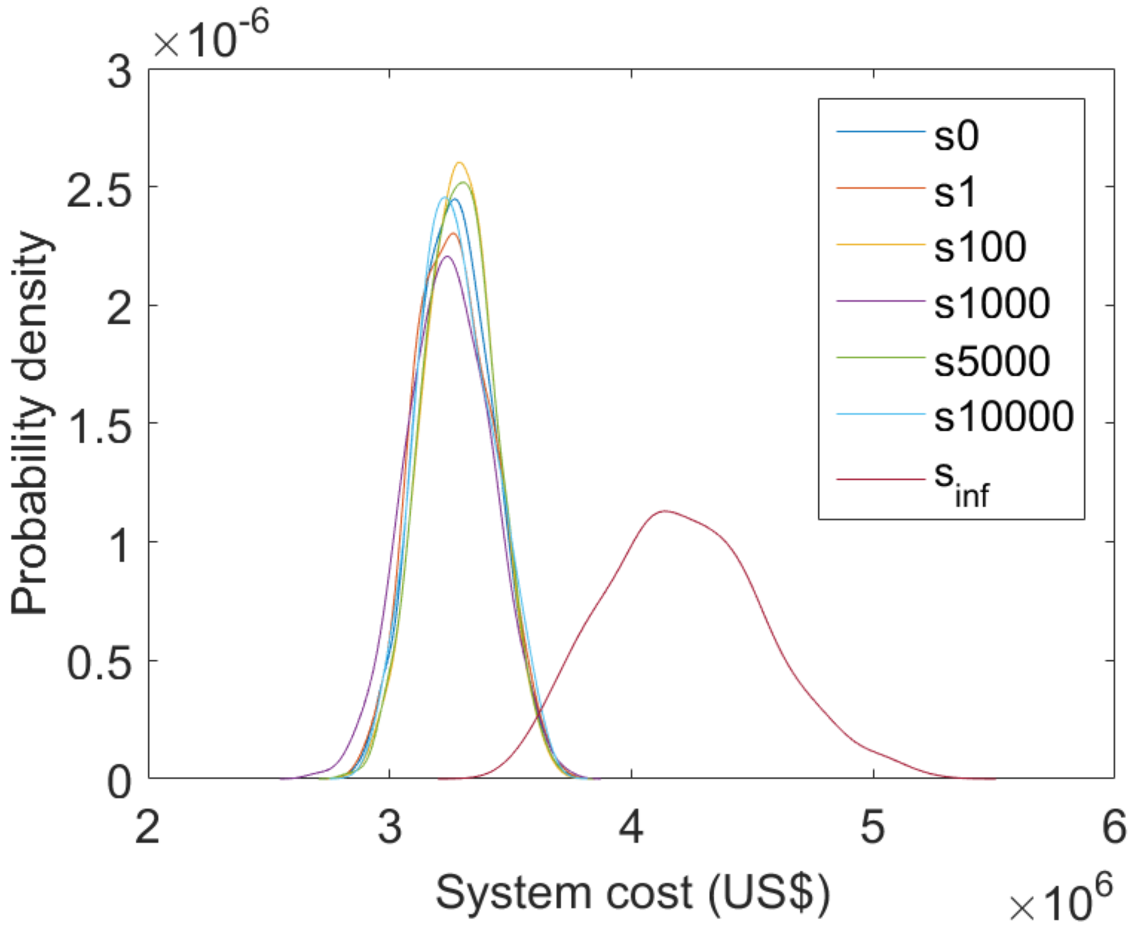

Figure 6-7. Disruption of cost from multiple perspectives with penalty for delayed berthing ranging from 0 to infinity.

Table 6-10. Summary statistics, including disruption coefficient from baseline, for system cost from multiple perspectives with penalty for delayed berthing ranging from 0 to infinity. Disruption coefficients marked * are not significant at a 0.05 confidence level.

Disruption ID	Disruption coefficient	Mean	Maximum	Minimum
s_0	-	$3.27 million	$3.72 million	$2.83 million
s_1	0.03*	$3.27 million	$3.71 million	$2.87 million
s_{100}	0.05	$3.29 million	$3.70 million	$2.83 million
s_{1000}	0.08	$3.24 million	$3.73 million	$2.69 million
s_{5000}	0.05	$3.29 million	$3.72 million	$2.83 million
s_{10000}	0.04*	$3.28 million	$3.67 million	$2.90 million
s_{inf}	0.96	$4.22 million	$5.23 million	$3.47 million

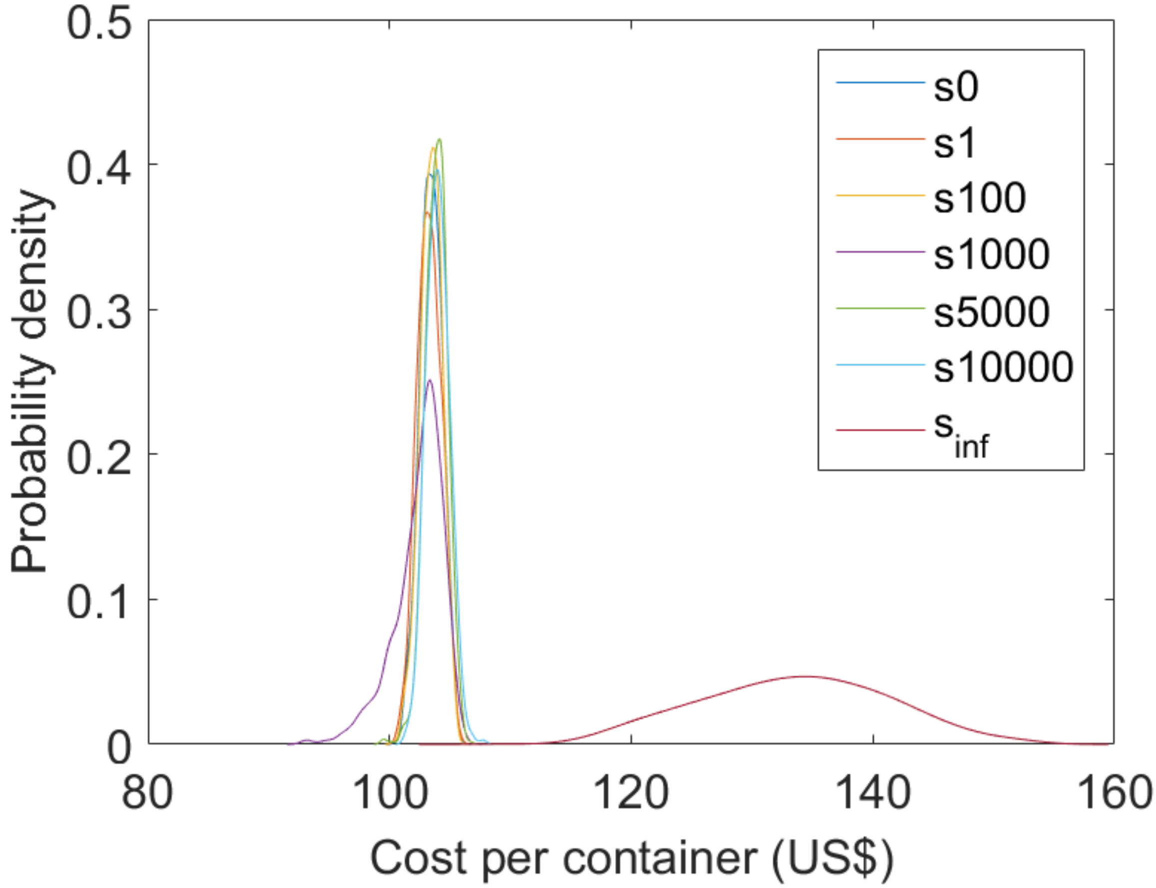

Figure 6-8. Comparison of cost per container distributions with disruptions from multiple perspectives with penalty for delayed berthing ranging from 0 to infinity.

Table 6-11. Summary statistics, including disruption coefficient from baseline, for cost per container from multiple perspectives with penalty for delayed berthing ranging from 0 to infinity. Disruption coefficients marked * are not significant at a 0.05 confidence level.

Disruption ID	Disruption coefficient	Mean	Maximum	Minimum
s_0	-	$103	$106	$100
s_1	0.07	$103	$106	$101
s_{100}	0.03*	$103	$106	$100
s_{1000}	0.29	$102	$106	$93
s_{5000}	0.19	$104	$107	$99
s_{10000}	0.20	$104	$108	$101
s_{inf}	1.00	$133	$153	$109

The system delays are illustrated in Figure 6-9 and summary statistics are shown in Table 6-11. System delays decrease with the increase of hourly penalty imposed on delays. As can be seen in the latter part of the figure, s_0, s_1, and s_{100} are the only disruptions what have mean delays over 4 hours (1 time period in the optimization model). Starting with s_{100} and continuing with increasing penalties, the system delays have at least a 0.99 disruption coefficient from the baseline s_0.

Terminal berth utilizations are illustrated in Figure 6-10 to Figure 6-12 and Table 6-12 to Table 6-14. NIT utilization, has a mean in the range of 0.31 to 0.35 for all disruptions, with generally slightly higher disruption coefficients as penalties for delays increase. The delay minimization disruption, s_{inf}, has the highest mean, although not dissimilar to other scenarios but the range between minimum and maximum is larger than for other disruptions.

VIG utilization is much lower for delay minimization, s_{inf}, than for other disruptions, whether it is mean, minimum, or maximum. While the mean ranges from 0.78 to 0.83 for other disruptions, it is 0.39 for s_{inf}. This is a result of the favorable berthing costs at VIG not being taken into account in that disruption whereas in others it is a major driver of the high utilization.

PMT utilization is around a 0.10 mean for $s_0 - s_{10000}$. However, for s_{inf}, the mean is similar to VIG and NIT, or 0.34, since the high berthing costs are not included in the objective.

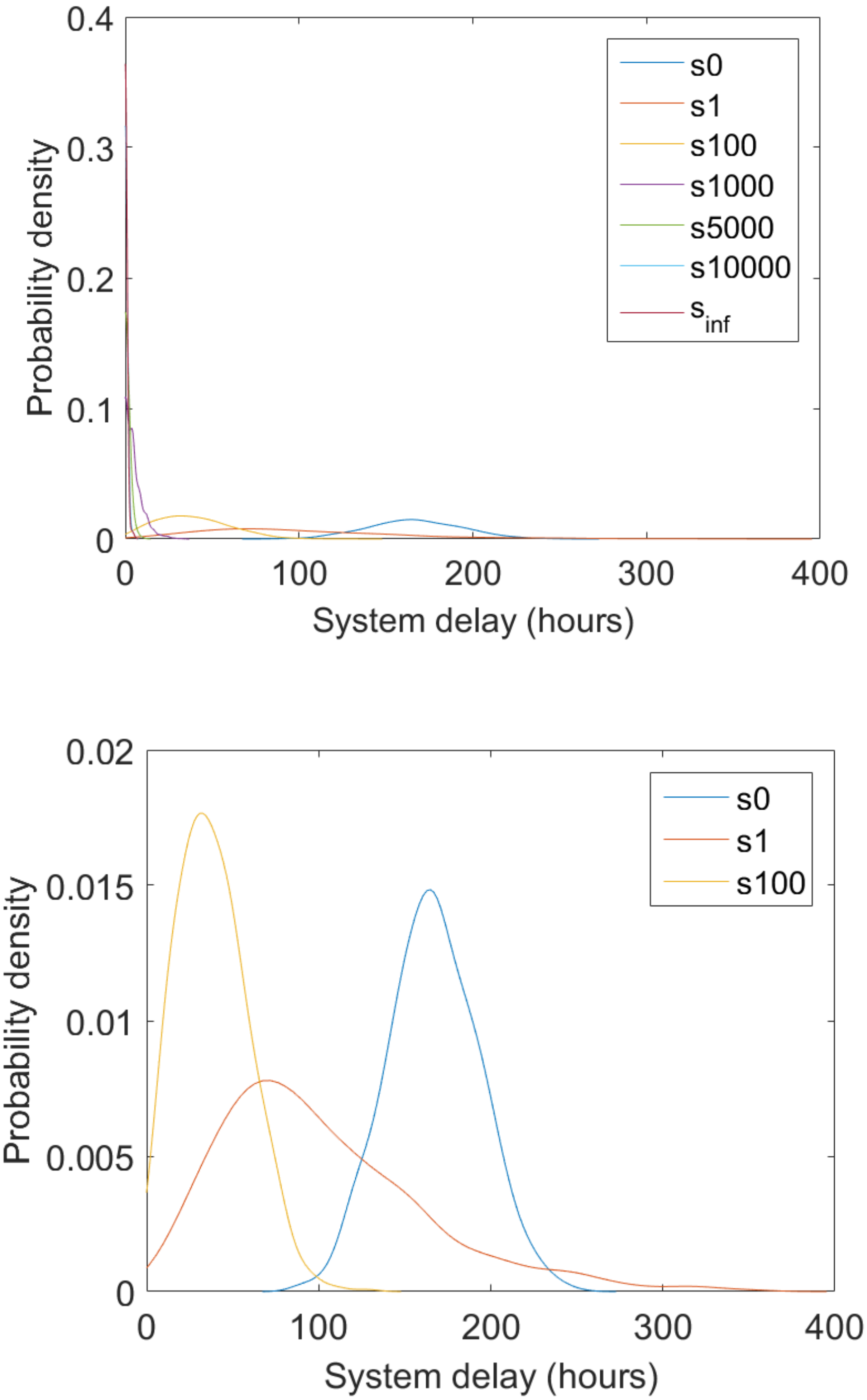

Figure 6-9. System delays distribution for multiple perspectives with penalty for delayed berthing ranging from 0 to infinity, including a zoom in on three disruptions with longest delays.

Table 6-12. Summary statistics, including disruption coefficient from baseline, for system delay from multiple perspectives with penalty for delayed berthing ranging from 0 to infinity.

Disruption ID	Disruption coefficient	Mean	Maximum	Minimum
s_0	-	167 h	252 h	88 h
s_1	0.67	101 h	352 h	0 h
s_{100}	0.99	38 h	128 h	0 h
s_{1000}	1.00	4 h	32 h	0 h
s_{5000}	1.00	0.3 h	8 h	0 h
s_{10000}	1.00	0.06 h	4 h	0 h
s_{inf}	1.00	0.06 h	4 h	0 h

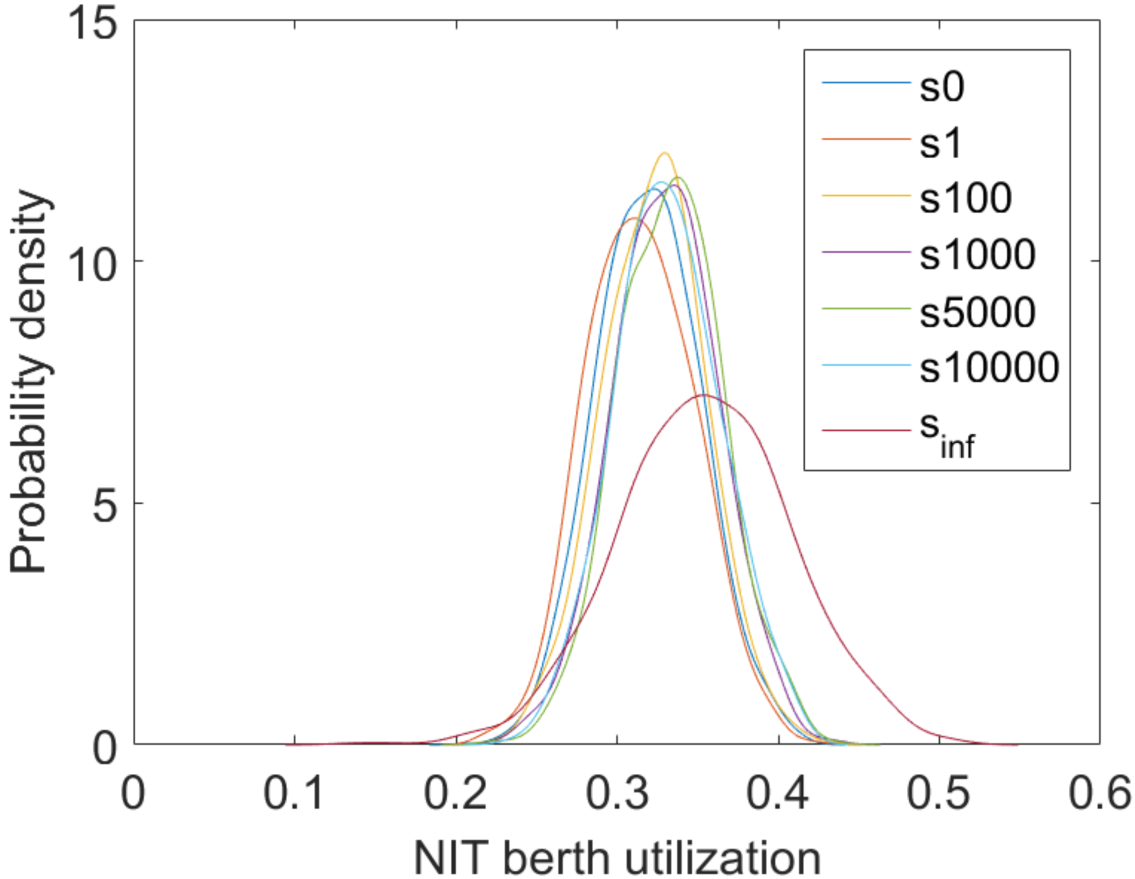

Figure 6-10. NIT berth utilization distributions for multiple perspectives with penalty for delayed berthing ranging from 0 to infinity.

Table 6-13. Summary statistics, including disruption coefficient from baseline, for NIT berth utilization from multiple perspectives with penalty for delayed berthing ranging from 0 to infinity.

Disruption ID	Disruption coefficient	Mean	Maximum	Minimum
s_0	-	0.32	0.42	0.21
s_1	0.07	0.31	0.42	0.22
s_{100}	0.05	0.32	0.43	0.23
s_{1000}	0.13	0.33	0.43	0.23
s_{5000}	0.17	0.33	0.43	0.22
s_{10000}	0.13	0.33	0.41	0.24
s_{inf}	0.37	0.35	0.51	0.14

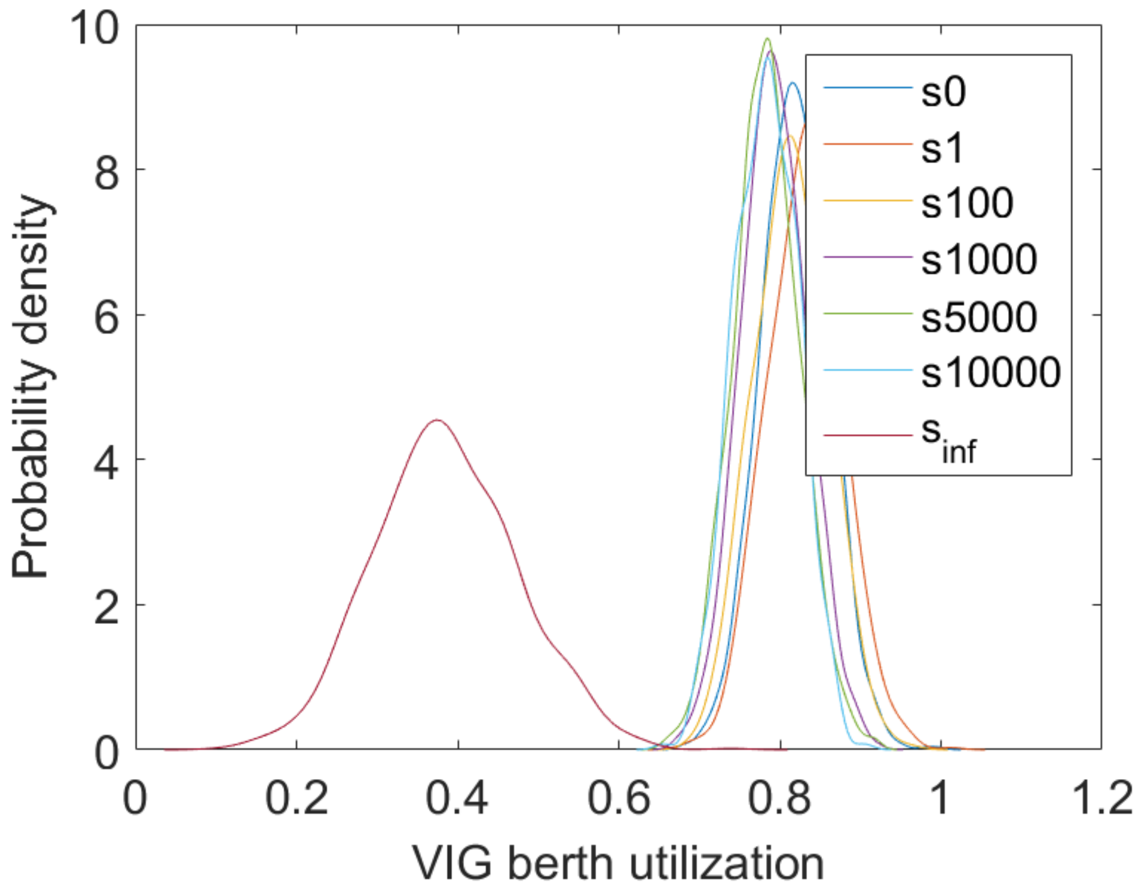

Figure 6-11. VIG berth utilization distributions for multiple perspectives with penalty for delayed berthing ranging from 0 to infinity.

Table 6-14. Summary statistics, including disruption coefficient from baseline, for VIG berth utilization from multiple perspectives with penalty for delayed berthing ranging from 0 to infinity.

Disruption ID	Disruption coefficient	Mean	Maximum	Minimum
s_0	-	0.82	1.00	0.68
s_1	0.12	0.83	1.00	0.68
s_{100}	0.06	0.81	0.96	0.69
s_{1000}	0.24	0.79	0.92	0.68
s_{5000}	0.32	0.78	0.92	0.65
s_{10000}	0.31	0.78	0.90	0.65
s_{inf}	1.00	0.39	0.74	0.11

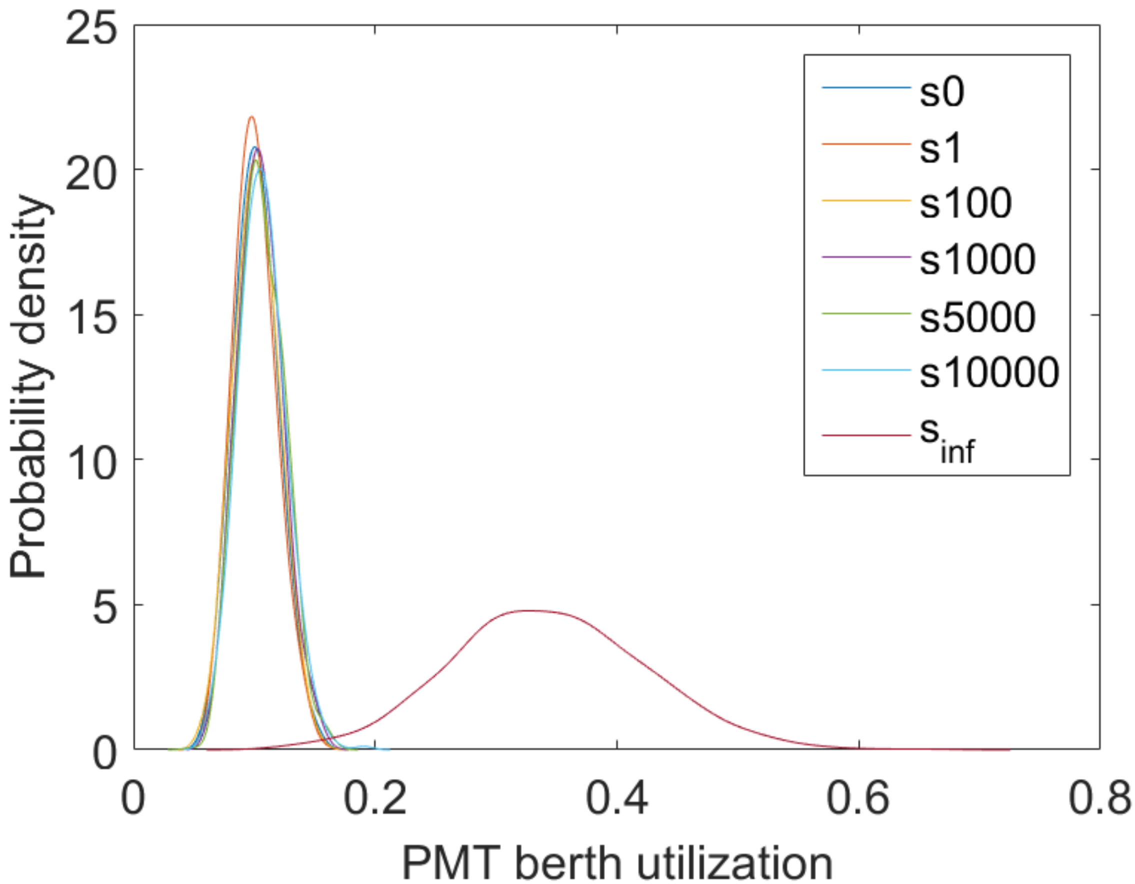

Figure 6-12. PMT berth utilization distributions for multiple perspectives with penalty for delayed berthing ranging from 0 to infinity.

Table 6-15. Summary statistics, including disruption coefficient from baseline, for PMT berth utilization from multiple perspectives with penalty for delayed berthing ranging from 0 to infinity. Disruption coefficients marked * are not significant at a 0.05 confidence level.

Disruption ID	Disruption coefficient	Mean	Maximum	Minimum
s_0	-	0.10	0.16	0.06
s_1	0.04*	0.10	0.16	0.06
s_{100}	0.02*	0.10	0.16	0.06
s_{1000}	0.06	0.10	0.16	0.06
s_{5000}	0.08	0.11	0.17	0.05
s_{10000}	0.10	0.11	0.19	0.06
s_{inf}	0.99	0.34	0.66	0.13

The seven perspectives have different terminal assignment probabilities. Starting before performing the optimization and simulation, it can be assumed that there is a 1/3 probability that a particular vessel is assigned to a particular terminal. With the purpose of quantifying how much information about assignments is gained by the analysis (alternatively how much uncertainty is reduced), Kullback-Leibler divergence is calculated between the resulting terminal assignment probability matrix of each perspective and a matrix where all probabilities are 1/3. These values are shown in Table 6-15. With the exception of the baseline, s_0, the information gain decreases with higher delay penalties, from 0.73 to 0.18 on a scale ranging from 0 (no information gain) to 1 (no uncertainty about assignments).

The discussion of results in this chapter has so far focused on individual performance measures and their disruptions when various penalties are added for schedule delays. Figure 6-13 shows, in three parts, the tradeoffs between system cost, system delays, and schedule information gain as quantified by Kullback-Leibler divergence. Interpreting the upper two parts, cost is close to constant for the various levels of both system delays and information gain, with the exception of the delay minimization disruption, s_{inf}. This indicates that to minimize delays, it is not necessary to add operational cost. However, an interesting tradeoff is between the reduction of delays and how needed flexibility of terminal assignments. The more delays are reduced, the less likely it is that vessels are assigned to the same terminals for various random arrival times, container volumes, and handling times.

Table 6-16. Schedule information gain for multiple perspectives of schedules with different delay penalties.

Perspective	Information gain
s_0	0.60
s_1	0.73
s_{100}	0.69
s_{1000}	0.49
s_{5000}	0.44
s_{10000}	0.43
s_{inf}	0.18

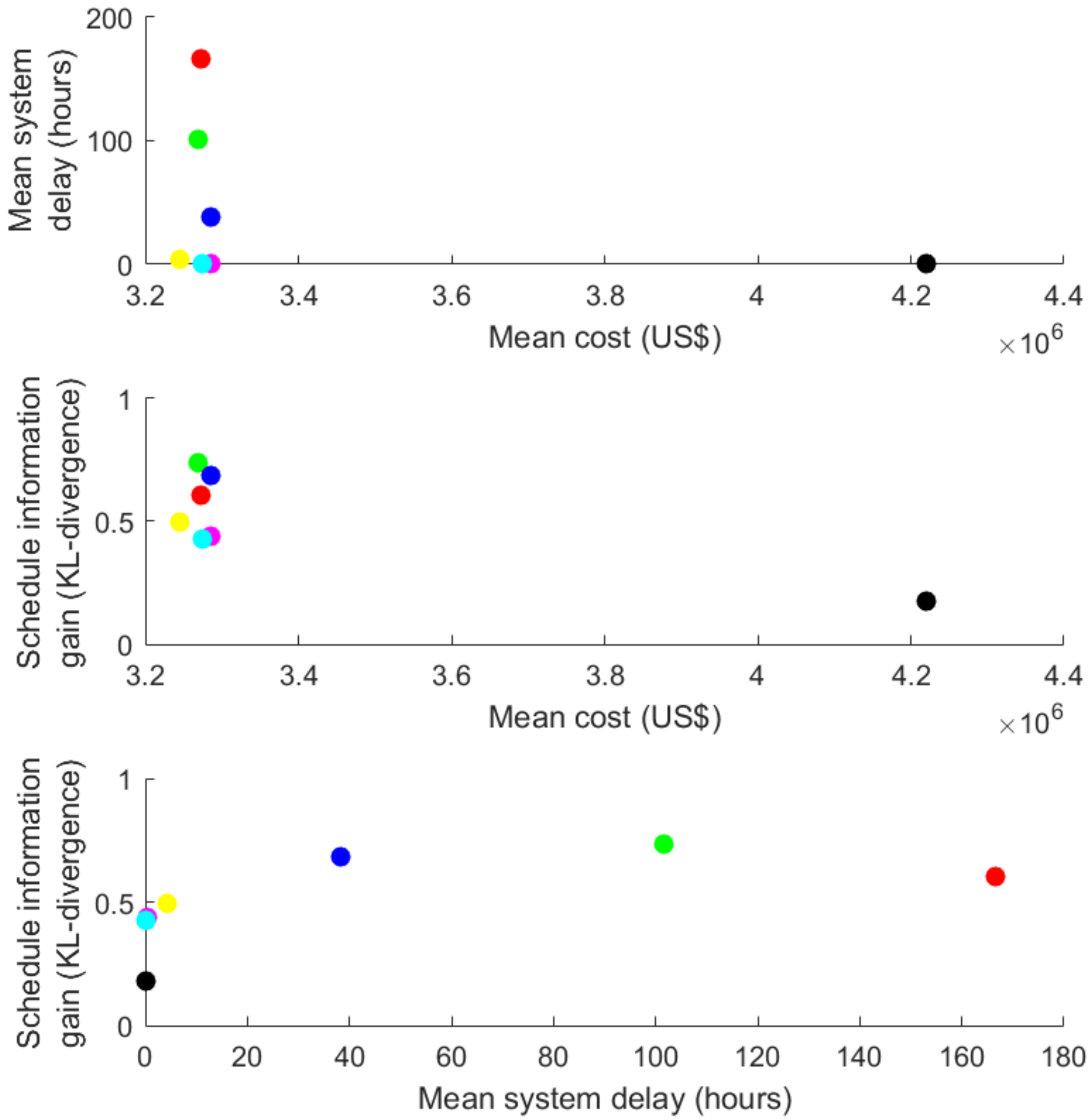

Figure 6-13. Tradeoffs between mean system cost, mean system delays, and schedule information gain for multiple perspectives. ($\boldsymbol{s_0}$ = red, $\boldsymbol{s_1}$ = green, $\boldsymbol{s_{100}}$ = dark blue, $\boldsymbol{s_{1000}}$ = yellow, $\boldsymbol{s_{5000}}$ = purple, $\boldsymbol{s_{10000}}$ = light blue, $\boldsymbol{s_{inf}}$ = black)

Summary

This chapter analyzed schedules that included varying levels of penalties associated with delays of vessels. It explored the extreme cases where no penalties are on delays and where minimizing delay is the sole objective. The results demonstrate that it possible to impose penalties to delays without dramatic increases in operational costs resulting from a higher level of assignments to more expensive terminals. However, reducing delays by adding penalties comes with a need for more flexible schedules, which may be contractually and operationally more difficult than when assignments are more stable across the various random arrival times, container volumes, and handling times.

This chapter is in part subject of a publication in IEEE Systems Journal, Reliability Engineering and Systems Safety, or another journal in the field of systems engineering, risk analysis, or multiple objective decision making.

Chapter 7

Demonstration: Disruptions of time frames

Overview

This section describes an approach for long term scheduling with uncertainty, as summarized in Table 7-1. The section describes the generalized assignment model for scheduling, Monte-Carlo simulation to address uncertainty in model inputs, a heuristic to filter and reduce the space of schedule options, and an evaluation of remaining schedules (Thorisson et al. 2019b).

Background

The vessel scheduling model described in previous chapters is designed for a single cycle of operations. With each instance of arrivals and volumes, there is a different optimal solution. In many instances, it is beneficial to formulate a schedule that is fixed for multiple operations cycles, in the case of vessel berth scheduling multiple weeks or months. The time frame in scheduling and decision making has been identified as a critical element (Haimes, 2012).

Table 7-1. Overview of Chapter 7, demonstrating schedule option development and disruptions from multiple time frames.

Chapter objective	Extending scheduling methodology to longer time horizons
Motivation	Re-optimization every time period (e.g. week) might be difficult in practice
Approach and data	Enumeration and filtering of schedule options informed by optimization and simulation results
	Evaluation of schedule options for tradeoffs of operational costs and delays using Monte Carlo simulation
Contributions	Approach for formulation of long term schedules informed by modeling and simulation
	Identification of tradeoffs between operational cost and delays for schedule options

Technical approach

This section describes an approach for creation and filtering of vessel berthing schedules, informed by the optimization and simulation methodology first presented in chapter 4. The approach includes formulation of the optimization model, motivation for Monte Carlo simulation and subsequently enumeration and filtering of schedule options.

Figure 7-1 shows the approach in a flowchart format. The parts added in this chapter are the filtering of schedule options using thresholds and subsequently evaluating the remaining schedule options.

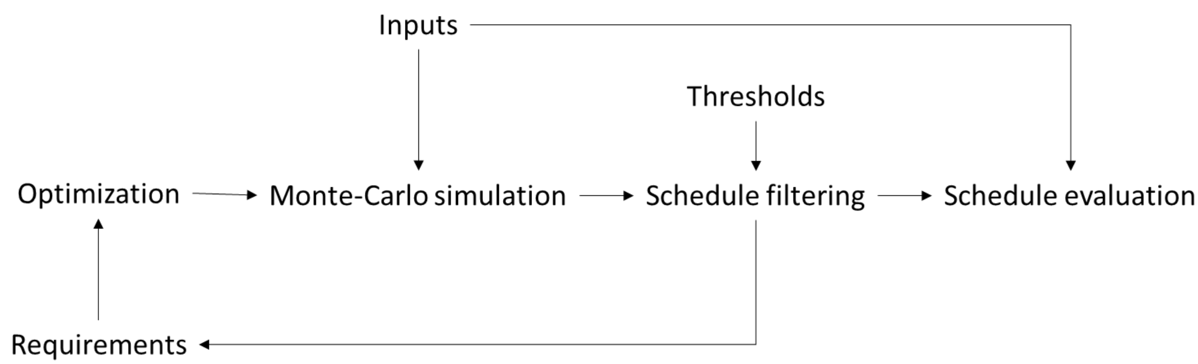

Figure 7-1. Flowchart of technical approach to creating schedule options informed by simulation and optimization of operational objectives.

The optimization and Monte Carlo simulation as well as inputs are the same as described in chapter 4. It assigns container vessels to the three terminals at the Port of Virginia. The objective of the optimization is to minimize the operational cost and the Monte Carlo simulation captures the variability in inputs such as vessel arrival times, container volume, and handling times. The variability means that the optimal solution for various different inputs does not result in the same terminal assignment of vessels. Rather, assignments are represented by probabilities of certain vessel to terminal assignments. A baseline probabilistic assignment is illustrated in Table 7-1.

The probabilistic assignment model can be appropriate when vessels can be scheduled to a different terminal every week. However, there might be practical limitations to this. For example, some ocean carriers store empty containers at terminals and load them on vessels when there is a demand to move them to different ports. If a vessel does not have a consistent assignment to a specific terminal, there can be additional costs related to moving empty containers between terminals by truck. Therefore, it can be beneficial to have a vessel berth schedule that assigns vessels to the same terminal multiple consecutive weeks, while still respecting the variability in inputs.

Table 7-2. Proportions of instances where the assignment that minimizes cost places vessels at particular terminals.

	l1	l2	l3
n1	0.00	0.00	1.00
n2	0.19	0.81	0.00
n3	0.41	0.59	0.00
n4	0.99	0.01	0.00
n5	0.28	0.55	0.17
n6	0.43	0.11	0.46
n7	0.98	0.01	0.01
n8	0.99	0.01	0.00
n9	0.72	0.28	0.00
n10	0.90	0.10	0.00
n11	0.00	1.00	0.00
n12	0.22	0.78	0.00
n13	0.01	0.99	0.00
n14	0.31	0.69	0.00
n15	0.16	0.84	0.00
n16	0.02	0.98	0.00
n17	0.30	0.70	0.00
n18	0.19	0.39	0.42
n19	0.71	0.04	0.25
n20	0.74	0.04	0.22
n21	0.07	0.39	0.54
n22	0.14	0.86	0.00
n23	0.46	0.54	0.00
n24	0.42	0.58	0.00
n25	0.86	0.04	0.10
n26	0.00	0.97	0.03
n27	0.94	0.06	0.00
n28	0.01	0.05	0.94
n29	0.98	0.02	0.00
n30	0.05	0.95	0.00
n31	0.88	0.12	0.00

If all decision variables in an $n \times m$ assignment problem have a non-binary probability, i.e. $\{\forall x_{ij}: x_{ij} \in]0,1[\,\}$, there are a total of 2^{nm} possible combinations before constraining the schedule option space. For a relatively simple problem of assigning 10 vessels to 2 terminals this gives over a million possible decisions. It is therefore critical to limit the space of solutions such that decision-makers can consider the costs, benefits, and trade-offs of different alternative solutions. The results of the optimization and simulation can inform the constraining the schedule option space. The proposed heuristic requires subjective input on thresholds and error tolerances, as well as external requirements not represented in the optimization model.

In each iteration of the heuristic there are six parts:

1. Run the Monte-Carlo simulation for the vessel berth scheduling problem. Generate Bernoulli parameters p_{ij}.
2. Assign vessel i to terminal j when the probability of optimally assigning i to j is larger than or equal to a threshold V. Mathematically this is written as

$$p_{ij} \geq V \Rightarrow x_{ij} = 1,\ \forall(i,j) \tag{7-1}$$

3. Not assign vessel i to terminal j when the probability of optimally assigning i to j is smaller than or equal to a threshold W. That is

$$p_{ij} \leq W \Rightarrow x_{ij} = 0,\ \forall(i,j) \tag{7-2}$$

4. Restrict the number of vessels to be assigned to terminal j. Since it is assumed that X_{ij} follows a Bernoulli distribution with parameter p_{ij}, the sum of n such variables with different parameters follows a Poisson binomial distribution with a mean $\mu_j = \sum_{i=1}^{n} p_{ij}$ and variance $\sigma^2 = \sum_{i=1}^{n} p_{ij}(1 - p_{ij})$. In other words, the expected number of vessels

assigned to terminal j when schedule is optimized is the sum of the probabilities of each vessel being assigned to the terminal. Defining a scalar U, the number of vessels to be assigned to terminal j can be restricted to a range of U standard deviations from the expected number of vessels:

$$\sum_{i=1}^{n} p_{ij} \pm U\sqrt{\sum_{i=1}^{n} p_{ij}(1 - p_{ij})}\,,\ \forall j \tag{7-3}$$

5. Include other requirements. In application, there may be specific requirements that restrict the solution space further. An example is when a vessel can only be scheduled at a subset of terminals due to size of vessel, equipment available, labor contracts, or other reasons.
6. Evaluate the size of the problem, i.e. the number of schedule options after filtering in steps 2-5. If the number of schedule options is lower than a threshold, T, evaluate all options. Otherwise repeat steps 1-5, adding constraint to represent the assignments and other filtering made.

The goal of the filtering is to produce a number of candidate schedule options that are evaluated against the random inputs (A_{ij}, B_j, C_{ij}) as discussed in the following paragraphs.

The optimization and simulation and subsequent filtering results in a number of candidate schedule options. This part evaluates the schedule options against the random inputs, fitted from historical data, and records the outputs in terms of system cost and other performance measures. This is again done by Monte-Carlo simulation. However, a difference from the previous is that each schedule is considered fixed and not optimized for every sample of inputs. The purpose is to examine trade-offs between different objectives, including ones the schedule is not optimized for, as well as providing decision makers with alternatives. This adds value to recommendations from analysis by buffering against a single optimal solution being operationally infeasible due to a factor not included in the mathematical model.

Data

The proportions of instances that vessels are assigned to particular terminals in the Monte Carlo simulation, described in Table 7-1, are an estimate of the random assignment variables in the described in the generalized assignment model. Now, they are used to filter the set of schedule options, using the approach in the Technical approach section. Setting the thresholds $V = 0.8$ and $W = 0.2$, the vessels that have a random parameter $p_{ij} > 0.8$ are assigned to the respective terminal. Similarly, those with parameters $p_{ij} < 0.2$ are prohibited from being assigned to those terminals. Setting threshold $U = 1$, the number of vessels assigned to each terminal is prescribed to be within one standard deviation from the mean of the Poisson binomial sum of how many vessels should be assigned to the terminal. Table 7-2 describes the implications of the thresholds to the filtering of schedules.

With the thresholds, 18 of the 31 vessels are assigned to a terminal. The other 13 have been limited to either of two terminals and bounds have been put on how many vessels should be assigned to each of the terminals. Creating the schedules, the filtering narrows the set of admissible schedules to 8305. Without the filtering, only two vessels are always assigned to the same terminal and hence the subsequent evaluation would have to account for many more schedules.

Table 7-3. Candidate terminals which to assign vessels, informed by cost minimization and simulation.

	l1	l2	l3	**Terminal candidates**
n1	0.00	0.00	1.00	**l3**
n2	0.19	0.81	0.00	**l2**
n3	0.41	0.59	0.00	**l1, l2**
n4	0.99	0.01	0.00	**l1**
n5	0.28	0.55	0.17	**l1, l2**
n6	0.43	0.11	0.46	**l1, l3**
n7	0.98	0.01	0.01	**l1**
n8	0.99	0.01	0.00	**l1**
n9	0.72	0.28	0.00	**l1, l2**
n10	0.90	0.10	0.00	**l1**
n11	0.00	1.00	0.00	**l2**
n12	0.22	0.78	0.00	**l1, l2**
n13	0.01	0.99	0.00	**l2**
n14	0.31	0.69	0.00	**l1, l2**
n15	0.16	0.84	0.00	**l2**
n16	0.02	0.98	0.00	**l2**
n17	0.30	0.70	0.00	**l1, l2**
n18	0.19	0.39	0.42	**l2, l3**
n19	0.71	0.04	0.25	**l1, l3**
n20	0.74	0.04	0.22	**l1, l3**
n21	0.07	0.39	0.54	**l2, l3**
n22	0.14	0.86	0.00	**l2**
n23	0.46	0.54	0.00	**l1, l2**
n24	0.42	0.58	0.00	**l1, l2**
n25	0.86	0.04	0.10	**l1**
n26	0.00	0.97	0.03	**l2**
n27	0.94	0.06	0.00	**l1**
n28	0.01	0.05	0.94	**l3**
n29	0.98	0.02	0.00	**l1**
n30	0.05	0.95	0.00	**l2**
n31	0.88	0.12	0.00	**l1**
Mean vessel assignments	**13.3**	**13.5**	**4.0**	
Std. vessel assignments	**3.1**	**3.0**	**1.1**	

Results

The 8305 schedules are the result of listing and filtering a probabilistic formulation of a schedule derived from an optimization and simulation approach. Since it is desirable to keep the same schedule for an extended time horizon, opposed to re-optimizing every week, the schedules are evaluated against the same random inputs that were used in the optimization instances. The evaluation reports the cost, total system delays, as well as delays by terminal and by vessel. This allows decision makers to compare the potential trade-offs between the cost of handling vessels as economically as possible with delays incurred by the shipping lines, and how delays are distributed across terminals and individual vessel services. The 8305 scheduled are evaluated, each for 1000 instances of random arrival times, container numbers, and handling times. Figure 7-2 illustrates the mean cost plotted against the mean delays of the schedules. The figure demonstrates there is a correlation between the cost and total delays, such that for a higher cost of operations, the mean delay incurred by vessels can be decreased.

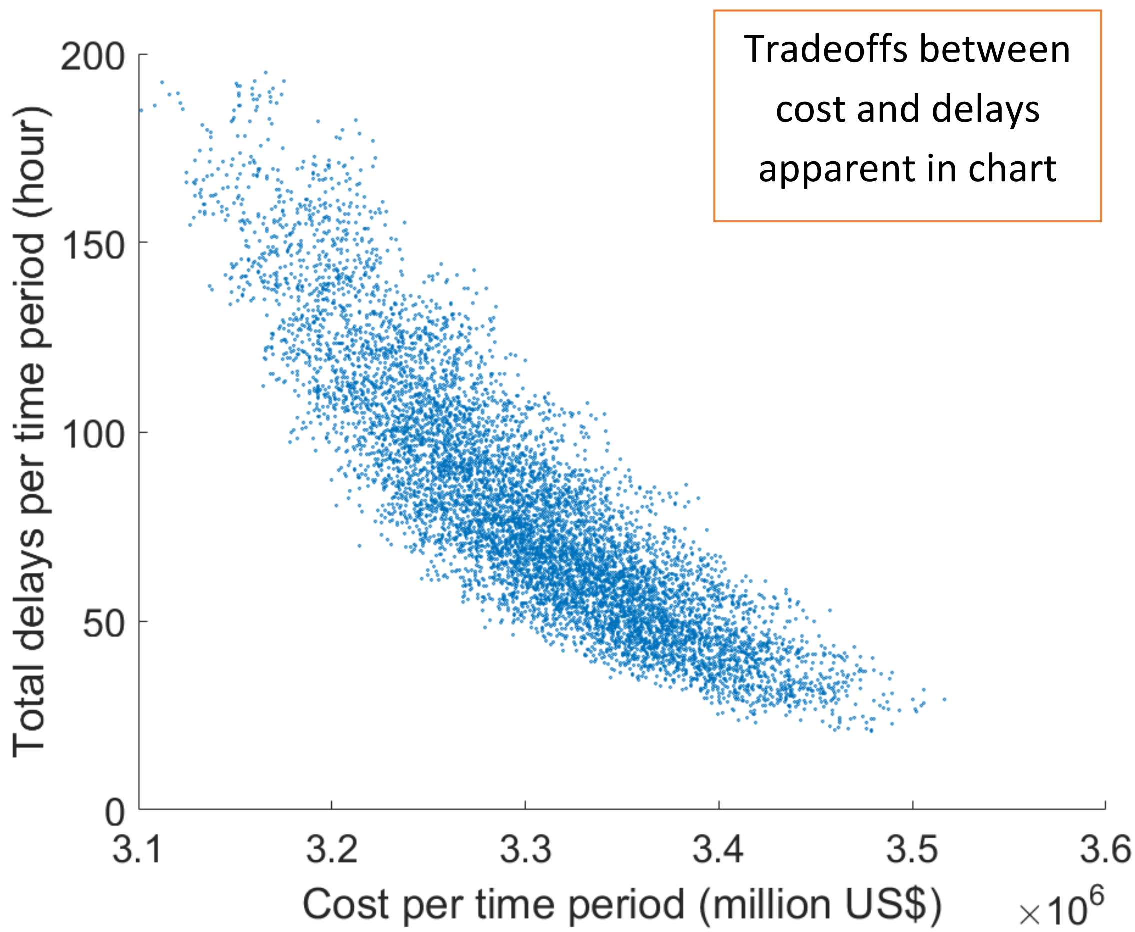

Figure 7-2. Evaluation of mean cost and mean delays for 8305 schedule options.

As Table 4-2 described, terminal VIG has the lowest per-container cost for all three handling modes and a high utilization at the terminal can be expected to contribute to lower overall handling costs. However, the high utilization creates potential for delays to accumulate at the terminal. Figure 7-3 shows the schedule delays by terminal, illustrated by boxplots. Terminal VIG has the most delays by a significant margin. Figure 7-4 shows the delay distribution by individual vessel. Of the ten vessels with the highest mean delay, all are either always assigned to VIG or is assigned to either VIG or another terminal. This calls for other performance measures, beyond the mean cost and mean delays, to be considered when choosing a schedule.

Figure 7-5 illustrates the tradeoffs between three schedules. The tooltips on the figure show the mean cost (in US$), mean delay (in hours/week), and the index of the schedules. The schedule to the far right (#1520) has the lowest delays of all schedules. The schedule to its left (#1172) has the lowest mean delay by vessel among all candidate schedules. This reflects the goal of minimizing discrimination between vessels in terms of scheduling to drive system performance in terms of mean cost and delays. The leftmost schedule (#2325) represents a non-dominated schedule that has a medium balance between mean cost and delays. Table 7-4 summarizes performance of the three schedules and trade-offs among them.

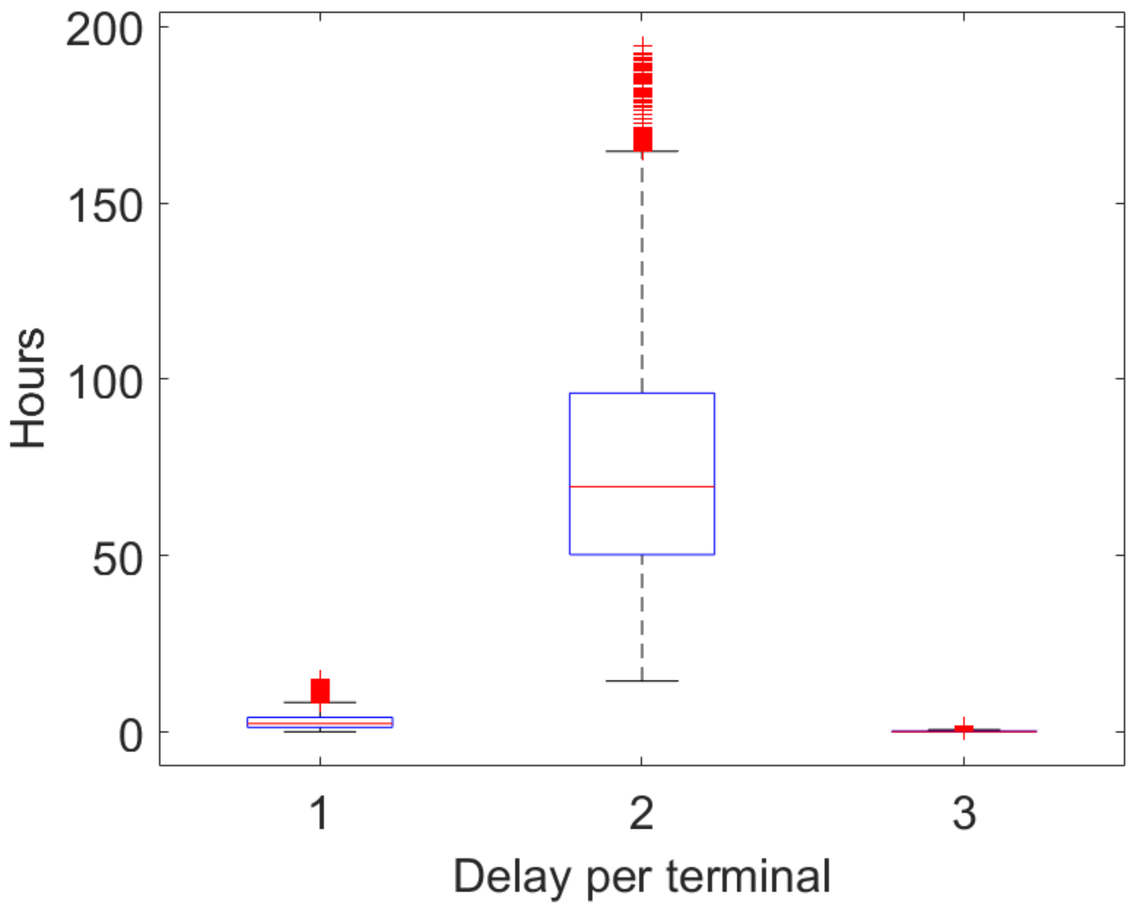

Figure 7-3. Distribution of delay by terminal (NIT, VIG, PMT) for 8305 schedule options.

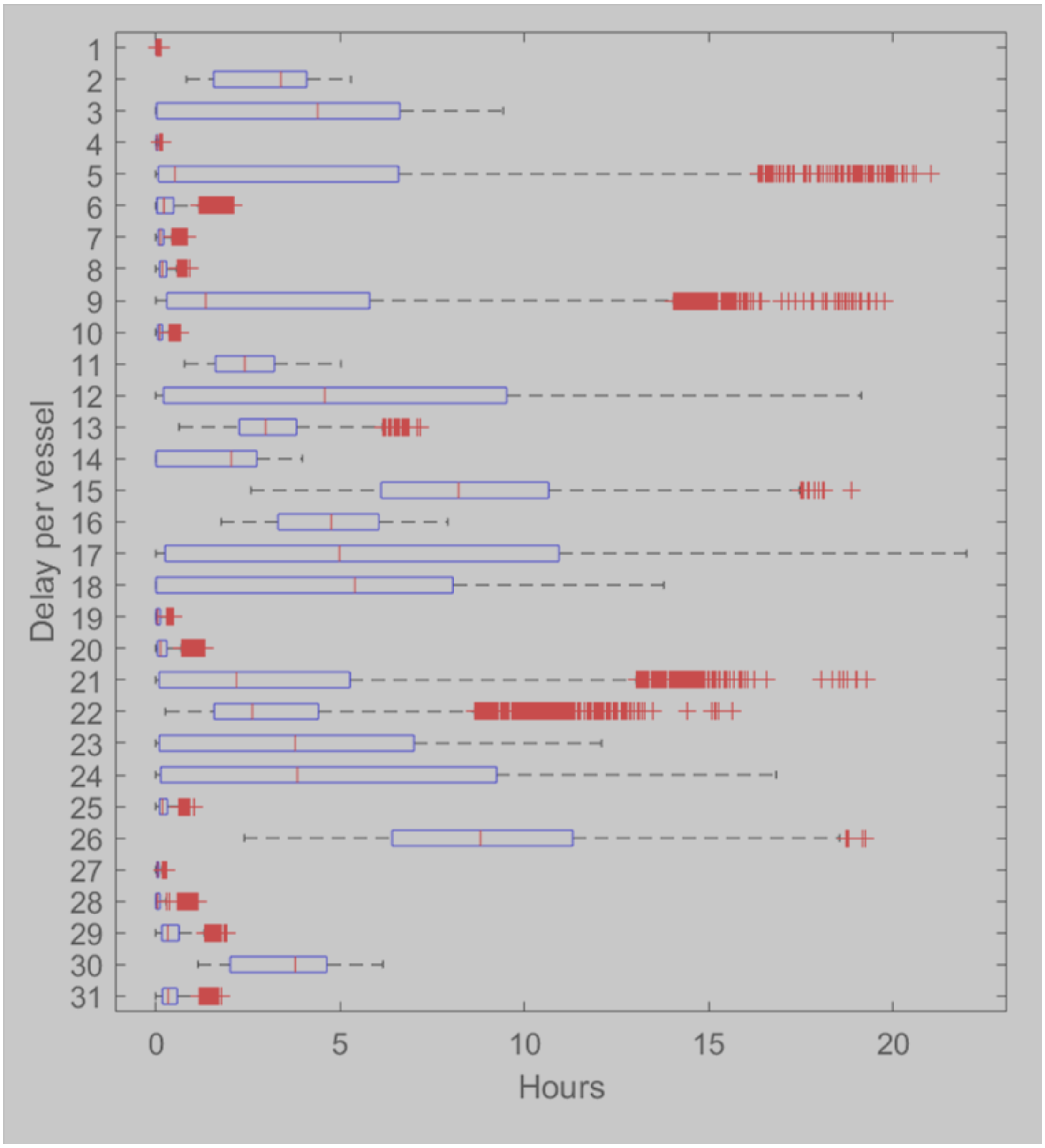

Figure 7-4. Distributions of delay by 31 vessel for 8305 schedule options.

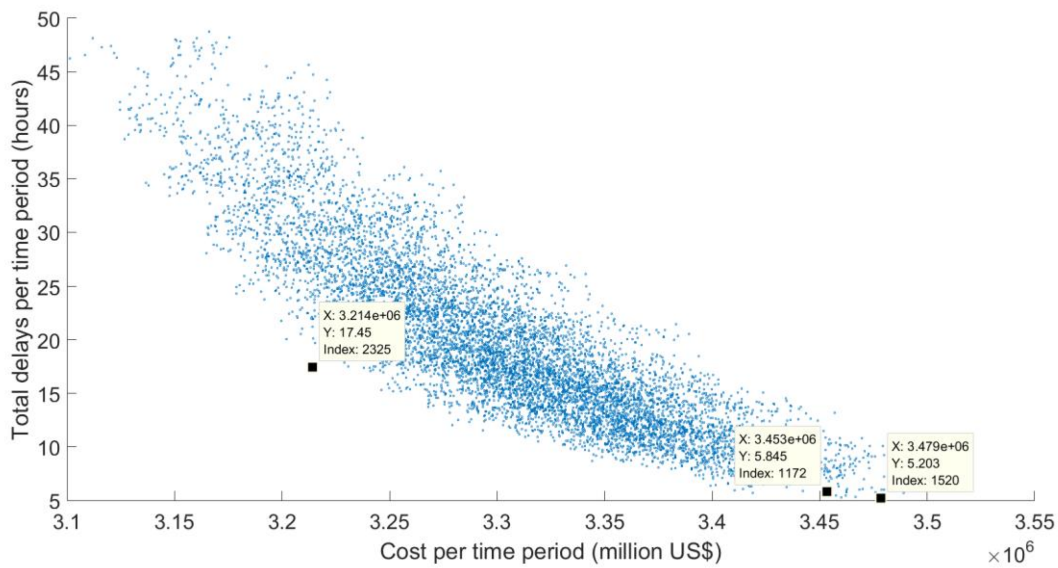

Figure 7-5. Example of three different schedule option performance and tradeoffs.

Table 7-4. Comparison of performance of a sample three schedule options on three criteria: Mean cost, mean delay, and lowest vessel mean delays.

Schedule ID	Mean cost (million US$)	Mean system delays (hours/week)	Lowest vessel mean delays (hours/week)
1520	3.48	5.2	2.8
1172	3.45	5.8	2.7
2325	3.21	17.5	8.1

Comparing schedule #1520 with #1172, the former has a $30,000 higher weekly cost but a mean of 0.6 hours shorter system delays. Even though #1172 has a lower maximum vessel mean delay, the different is not greater than 0.1 hours. Schedule #2325 has a cost that is $340,000 less than schedule 1172, but a mean system delay of over 17 hours. Looking only at the two performance measures, this equates to a trade-off of about $28,000 per hour delay. However, the delays of schedule #2325 are not distributed evenly. Eight of the 31 vessels incur on average over four hours of delay, with the largest average being 8.1 hours. Thus this could be a viable schedule alternative, if decision makers believe it is feasible to operate this schedule without losing the business, or at least customer satisfaction, of the vessels incurring consistent delays.

The shipping industry is under increasing pressure to operate more efficiently and be resilient to changes in demand, markets, technology, and the environment. The expansion of the Panama Canal has created opportunities for larger vessels to serve global routes [Friedman 2017]. Larger vessels require deeper ports and ports around the globe are challenged to update their facilities while maintaining an acceptable service level.

Based on review of trade literature [Mofatt and Nichol 2016; Bratton et al. 2015; Rodrigue 2010] and discussions with shipping professionals, three disruptions along with the baseline scenario are considered. Table 7-4 describes the disruptions. Disruption 1, d_1, represents partial closure of the facility due to construction, accidents, or other planned and unplanned outages. It is implemented by having three berth positions at terminal NIT, rather than four as in the baseline. Disruption 2, d_2, explores the implications of higher container volumes being handled at the port. This is a representation of both annual cycles, such as increased imports before holidays, as well as longer term trends. Disruption 3, d_3, is a combination of $d_1$and d_2 which represents a condition where both volumes are high and operating capacity is limited.

Table 7-5. Disruptions for vessel schedule options development.

	Disruption name	Description
d_0	Baseline	The as-planned scenario
d_1	Closure of a NIT berth	NIT has three berths available rather than four
d_2	Higher demand for container handling	Baseline of containers handled by each vessel are increased by 25%
d_3	Closure of a NIT berth and higher demand for container handling	Combination of d_1 and d_2

Figure 7-6 plots the mean system delays against the mean system cost for the 8305 schedules for the baseline and the three disruptions. Unsurprisingly, the system cost increases significantly for all schedule options when the volume is increased by a factor of 25%. Since there is no re-optimization involved in the analysis, the cost per container is does not change due to higher volumes. System delays are disrupted both by increased volume and limited capacity.

Quantifying the disruptions of the system delay for the three disruptions, the disruption coefficients for schedule options in a particular are visualized in histograms in Figure 7-7. There is overlap between the disruption histograms, but disruption d_1 has the lowest mean disruption, then d_2, and the schedule options are most disrupted with regard to system delays in d_3. Disruption d_2 differs from the other two in terms of the variance of disruption coefficients. The minimum and mean are higher than that of d_1 but the maximum is lower than the maximum of d_1.

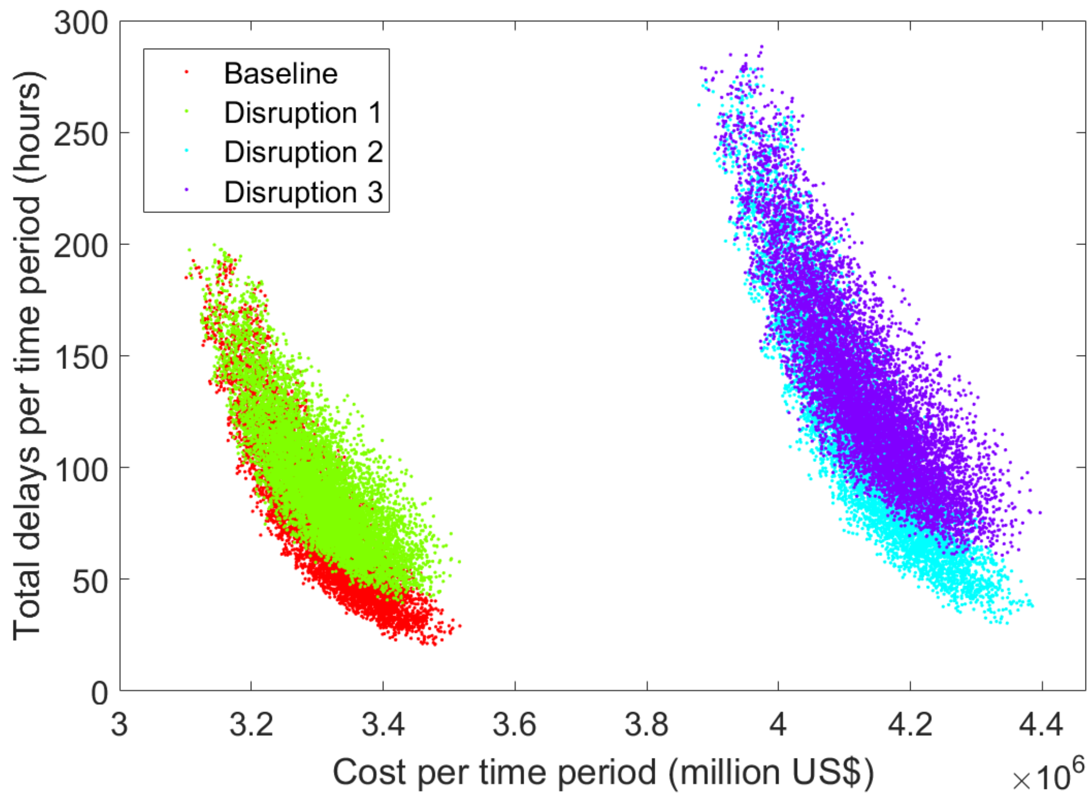

Figure 7-6. Mean cost versus mean total delays for a baseline and three disruptions for 8305 schedule options.

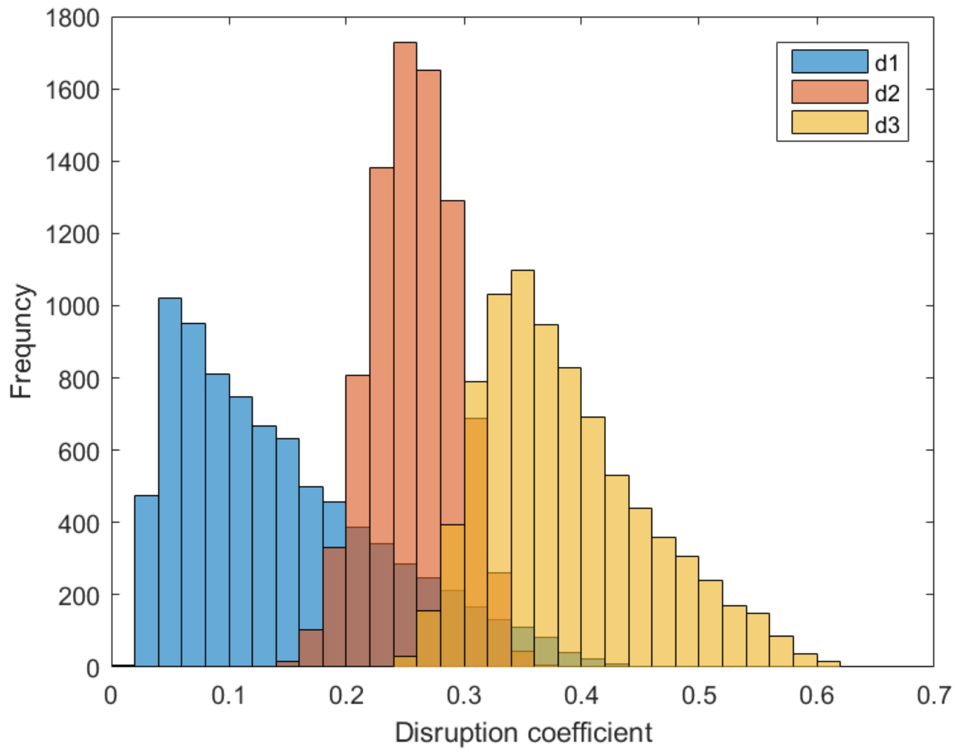

Figure 7-7. Disruption coefficients of system delays for schedule options in three disruptions.

Table 7-6. Summary statistics of disruption coefficients for system delays of schedule options in three disruptions.

Disruption	Mean disruption coefficient of schedule options	Maximum of disruption coefficient of schedule options	Minimum of disruption coefficient of schedule options
d1	0.14	0.46	0.01
d2	0.26	0.39	0.11
d3	0.39	0.62	0.24

Summary

This chapter demonstrates how the results from the Monte Carlo simulation and cost minimizing optimization for a one week time frame can be extended to create schedule options for a longer time frame. Schedule options are created and filtered as well as evaluated against random arrival times, container volumes, and handling times. Thus, performance of system cost and delays are analyzed in terms of robustness and expected performance. Of course, the above demonstration illustrates a sample of the insights that can be gained from applying the methodology to a scheduling problem. Constraints, thresholds, and other subjective inputs should be iterated and evolve with the operations and business environment.

This chapter has been published in part as:

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Chapter 8

Demonstration: Truck operation disruptions

Overview

This demonstration explores schedules of truck fleets that are disrupted by weather, surges in demand, and other conditions (Thorisson et al. 2018). Trucking companies are responsible for moving the majority of containers in and out of the port facilities and a smaller proportion is moved by rail or barges. Recently, congestion at ports on both the US East Coast and West Coast have exemplified the need for scheduling truck arrivals and services in a reliable manner to withstand disruptions. The results highlight the need for data quality and accounting for dependencies among system activities. Table 8-1 provides an overview of the chapter.

Table 8-1. Overview of Chapter 8, demonstrating disruptions of truck operations for two regimes of operations.

Chapter objective	Identify bottlenecks and characterize states of operation for trucks serving a marine container terminal
Motivation	Congestion at container terminals has been an issue in Virginia and beyond as the global shipping industry expands
Approach and data	Truck operations data at the Port of Virginia from 2015-16 is classified into the different states of operations
	Time spent and number of trucks in each state is compared for truck turntimes over and under 60 minutes
Contributions	Identification of states that contribute most to long turntimes and bottlenecks
	Considerations of downstream effects of vessel berth scheduling

Background

Maritime container ports are an important part of supply chains as ocean transportation is typically a cost-effective option for shipping commodities over long distances (Buxbaum, 2016). Ports are often owned or operated by the local governments and have missions that serve the public interest. They operate through economic and natural disruptions. Conditions at global levels (e.g., climate, macroeconomic trends, disruptive technological innovation) and regional/local levels (e.g., demographic shifts, region-level funding) affect the ability of ports to achieve their missions (ASCE, 2017). There is a need to find efficiencies, economies of scale, and innovations that allow these ports to achieve improved outcomes with fewer resources. Ports across the world are searching for innovative methods for obtaining financing, maximizing land use, and reducing risk through diversification of cargo types. It is essential that capital expenditures are leveraged in ways that return the maximum return on investment.

Port operations involve multiple groups and stakeholders, including port owners and operators, shipping lines, trucking companies, stevedores, rail companies and others. The various stakeholders all contribute to the overall performance of the port, and interdependencies can cause disruptions in one area, e.g. vessel arrivals, to propagate to another area, e.g. trucking. Vessel berthing and allocation of equipment to load and unload vessels has been studied extensively, e.g. (Alattar & Karkare, 2006; Alvarez et al., 2010; Bierwirth & Meisel, 2015; Cao, Lee, Chen, & Shi, 2010; Dragovic et al., 2006; Dulebenets et al., 2015; Stahlbock & Voss, 2008; Y. Xu et al., 2012). However, the landside part of operations, moving cargo from the terminal yard to locations further down the supply chain, has been identified as an understudied area (Harrison, Hutson, West, & Wilke, 2007). Port drayage refers to transport of cargo between a port terminal and an inland location (Smith, Harder, Huynh, Hutson, & Harrison, 2012). This chapter confines the term to container transport, although methods and conclusions are generalizable to other types of commodities.

Port drayage operations have received attention in recent years due to complaints of truck drivers about congestion within terminals as well as queueing at terminal gates (Hutchins, 2016; McCabe, 2015). Harrison et al (2007) conducted a survey among truck drivers receiving or delivering containers at the Port of Houston, USA, and found that 45.7% of drivers were unsatisfied with the efficiency of terminal operations, compared to 22.3% being satisfied or very satisfied. In addition to decreasing terminal efficiency with associated cost and less customer satisfaction, congestion also has negative effects on air quality, increases polluted runoff, and contributes to congestion on hinterland roads. In order to increase efficiency of operations and reduce other indirect negative effects, it is important to identify and resolve bottlenecks in truck throughput at terminals. Innovative methods such as webcam image processing (Huynh, Harder, Smith, Sharif, & Pham, 2011; Pham, Huynh, & Xie, 2011) and data mining (Huynh & Hutson, 2009) have been used to analyze gate queues and identify certain types of transactions that have abnormally slow processing times. However, there is a need to investigate further the specific contributions of activities such as queueing at gates, waiting for service at stacks, and receiving a chassis inspection to the overall performance of drayage operations.

This chapter investigates schedules, or lack or schedules, of truck arrivals at the Port of Virginia. For a background on the port, see Chapter 4.

This chapter demonstrates a framework for disaggregation of uncertainties of operations of large-scale systems into several layers, including a characterization of operations data for a container terminal on the United States East Coast, shown in Figure 8-1 and Figure 8-2. A method for analyzing the spatial and temporal stress on various areas within the terminal is developed, and factors driving this stress are delineated.

Figure 8-1. Approach to Virginia International Gateway terminal, a part of the Port of Virginia, USA (Port of Virginia, 2017).

Figure 8-2. Aerial view of Virginia International Gateway container terminal (Google Maps, 2017).

Technical approach

The efficiency of port drayage is in the industry typically measured by the *truck turn time*, that is how long it takes trucks to enter a terminal, perform required transactions, and leave the terminal. There is some variability between agencies how turn time is measured. In some cases it includes time waiting in line outside the terminal or if it includes the processing time at the gate entering. In this chapter, *traditional turn time* is defined as the time from when a truck enters the terminal yard until it leaves through the gate, whereas *expanded turn time* includes the time a truck spends queueing before entering the yard (Virginia Port Authority, 2015). Figure 8-3 and Figure 8-4 illustrate the definitions and illustrate the layout of the terminal and where time stamps are collected. While making a visit to the terminal, trucks can perform several types of transactions. *Ingate transactions* involve presenting necessary paperwork and entering the terminal yard. *Stack transactions* involve delivering containers for export or receiving containers for import. *Chassis transactions* involve getting a chassis inspected or repaired, picking up or dropping off an empty chassis. *Outgate transactions* involve presenting paperwork and leaving the terminal yard.

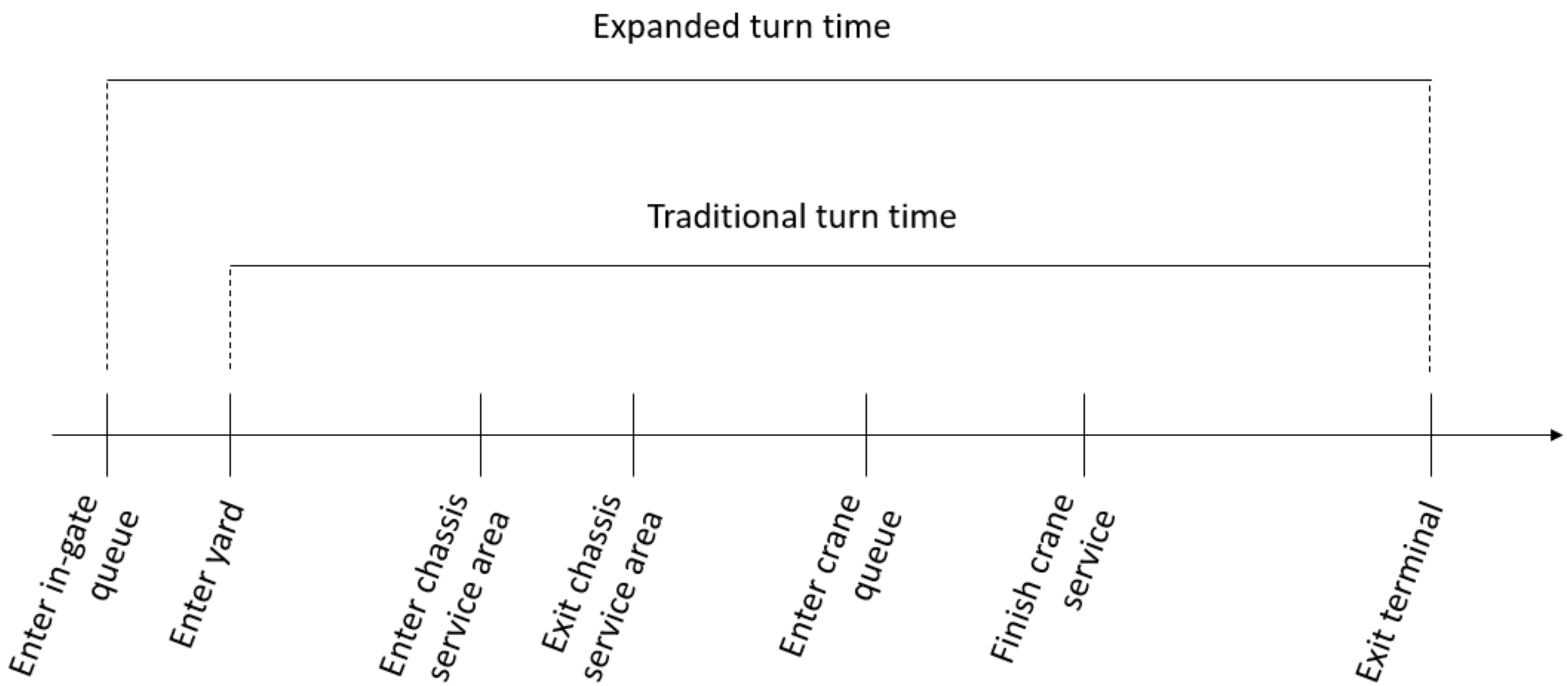

Figure 8-3. Traditional and expanded turn time in relation to activities performed during truck visit.

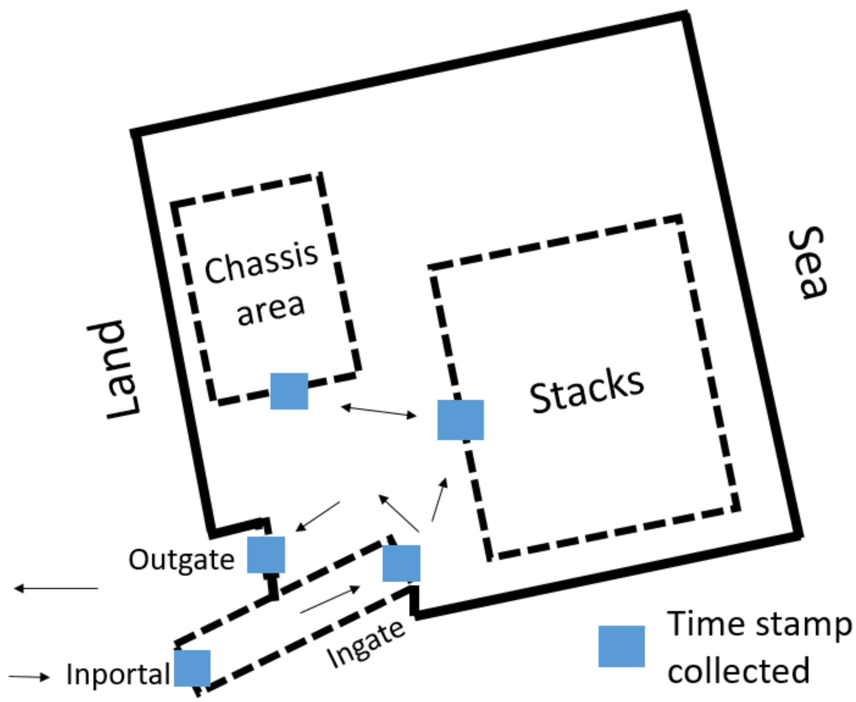

Figure 8-4. Layout of container terminal and locations of RFID time stamps collected on truck visits.

This demonstration characterizes operations data on truck visits at the Virginia International Gateway terminal. The terminal is one of five terminals of the Port of Virginia and is located in Portsmouth, Virginia, USA. Various data is collected on truck visits to the terminal. Using RFID readers several time stamps pertaining to the truck visit are recorded. Table 8-1 expands on Figure 8-3 and describes the time stamps. These time stamps are used to model the flow of truck traffic through the terminal. During a visit a truck can make multiple stack transactions, each with its own *LTADATE*, *LTACRANESTARTED*, and *LTACRANEFINISHED*. It should be noted that a given truck visit might not perform all types of transactions.

Table 8-2. Time stamps collected for truck visits at the container terminal.

Time stamp	**Description**
INPORTALDATE	Truck enters queue for terminal admission
INGATERAISEDATE	Truck enters terminal yard
LTADATE	Truck enters stack area
LTACRANESTARTED	Crane starts moving container from stack to truck
LTACRANEFINISHED	Crane finished moving container from stack to truck
FIRSTCSAINDATE	Start of first chassis service area entrance during visit
FIRSTCSAOUTDATE	End of first chassis service area entrance during visit
LASTCSAINDATE	Start of last chassis service area entrance during visit
LASTCSAOUTDATE	End of last chassis service area entrance during visit
OUTGATERAISEDATE	Truck leaves terminal yard

The relevant data collected at the terminal describes individual transactions. In order to get information about the various states of the system while operating in different regimes, the data must be transformed from the transactions domain to a turn-time domain. An entry in the database is created every ten minutes during the study period (entries can be adjusted to a shorter or longer period based on preferences of stakeholders). At the instance of the entry, the number of trucks in each states is recorded and the time the trucks currently in the system spend in their respective state as well as their traditional and expanded turn times. Thus, it is possible to correlate the time and occupancy of states with the overall turn time. States that are robust to variations in turn times can be expected to have a similar mean and variance in time and occupancy for different regimes of turn times.

To gain further insight to the behavior of the flow of trucks through the terminal, the transitions between states are modeled as a Markov chain. All trucks enter the system through the *ingate* and leave through the *outgate* but visits to *chassis area* and *stacks* can be in any order and multiple visits to these states are possible. In the demonstration presented, the number of visits to the *chassis area* and cranes does not exceed two. A key aim of the following analysis is to compare and contrast the prevalence of certain activities and their respective duration for different regimes of overall terminal drayage performance. The aim is to identify factors that drive long turn times and opportunities to improve operations, lower cost and improve customer experiences. The main distinction in the analysis is made between *long turn times*, where the traditional turn time is over 60 minutes, and *short turn times* with traditional turn times under 60 minutes.

Data

This section describes a demonstration of the methods described in the previous section. The setting of the demonstration is the Virginia International Gateway, a container terminal operated by the Port of Virginia in the Hampton Roads region of Virginia, USA. The terminal has the capacity to process over one million twenty-foot equivalent unit containers annually and is the first and one of very few operational *automated* container terminals in the Western Hemisphere, with semi-automatic rail mounted gantries moving containers between *stacks* and trucks (Virginia Port Authority, 2017). The terminal experienced significant congestion in early 2015 with excessive turn times and customer dissatisfaction (McCabe, 2015). Extended gate hours and several other measures were implemented and average turn times became shorter in the summer of 2015. A variety of macro-scale events have been tied to the period of excessive turn times, such as winter weather slowing down operations and labor disputes on the US West Coast driving more business to East Coast ports. However, analyzing on a within-terminal scale bottlenecks or distribution of service demand serves on important purpose to improve efficiency and being able to recognize warning signs for long turn times.

The daily average turn time for the study period, January to September 2015, is illustrated in Figure 8-5. There is an apparent seasonal behavior as Saturdays have shorter turn times than weekdays. During the study period the terminal was closed to truck traffic on Sundays. After turn times peak around day 50 there is a downward trend for the rest of the period. There are however still days towards the end of the period that exceed the operational goal of having turn times under 60 minutes. Figure 8-6 and Figure 8-7 illustrate the number of trucks and time spent in each state at a given instance. The *stacks* is the state that has the highest median number and time in state. Comparing the number of trucks with the time spent in states there are generally parallels. *Stacks*, *ingate* and *stacks queue* have the greatest spread, in terms of interquartile range, for both measures. The chassis state takes the shortest time and has the fewest trucks present. A noteworthy difference is that in the time view there are more outliers, observations that are further than 1.5 times the interquartile range from the 75th percentile.

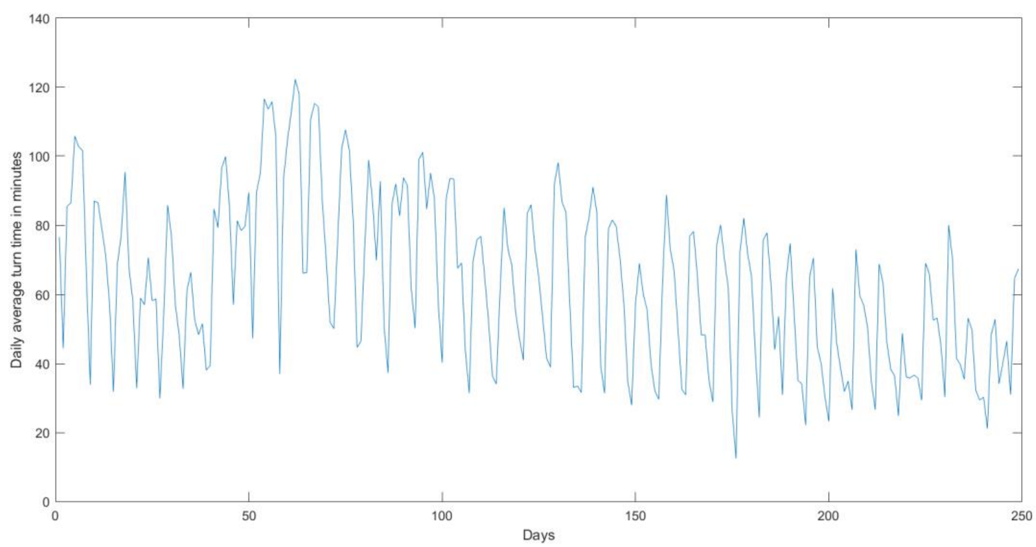

Figure 8-5. Daily average turn time of trucks at Virginia International Gateway over the study period, Jan 2015 - Sept 2015.

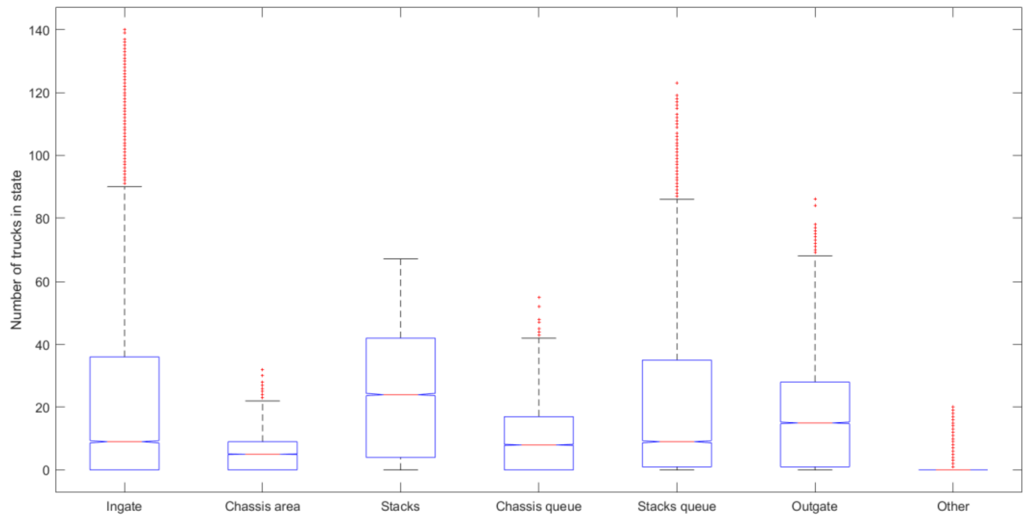

Figure 8-6. Distribution of the number of trucks in each state of a container terminal yard over a 9-month period.

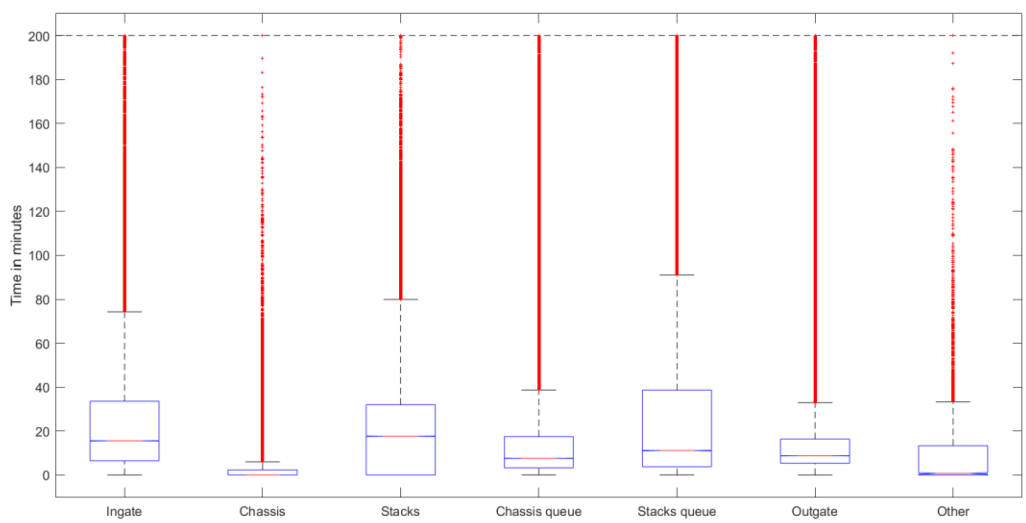

Figure 8-7. Distribution of time trucks spend in each state of a container terminal yard over a 9-month period.

Results

Figure 8-8 to Figure 8-10 compare and contrast the distributions of times and numbers in the several states between periods where average turntimes are under and over 60 minutes. Generally, when turn times are over 60 minutes the distributions are shifted to the right, meaning there are more trucks in each of the states and they spend longer time in states. Furthermore, the distributions for longer turn times have lower peaks so the number of trucks in states and the time spent in states is less predictable.

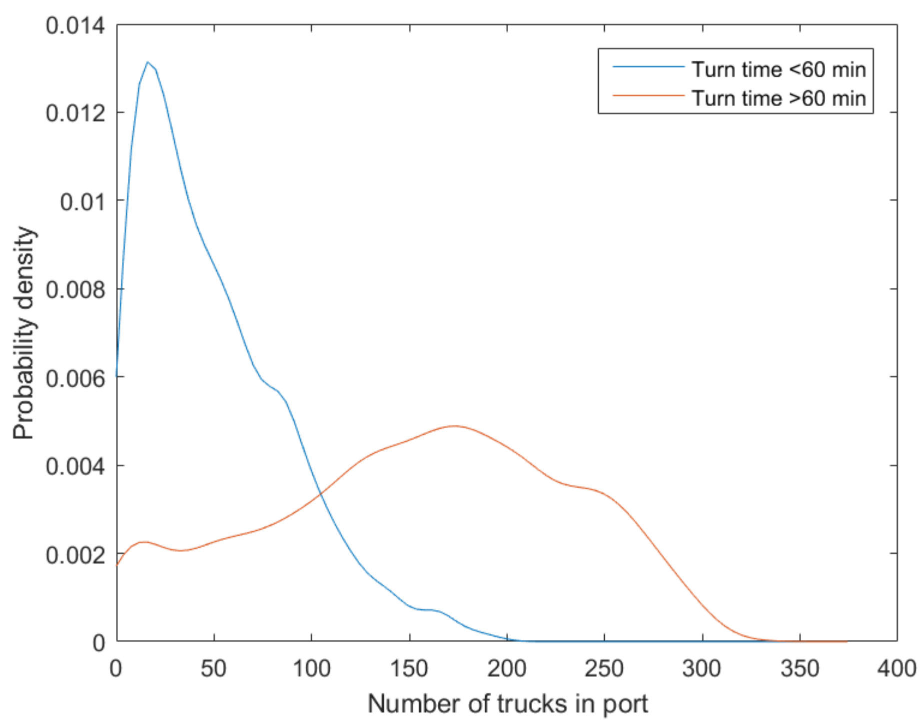

Figure 8-8. Distribution of the total number of trucks in port, grouped based on traditional turn time.

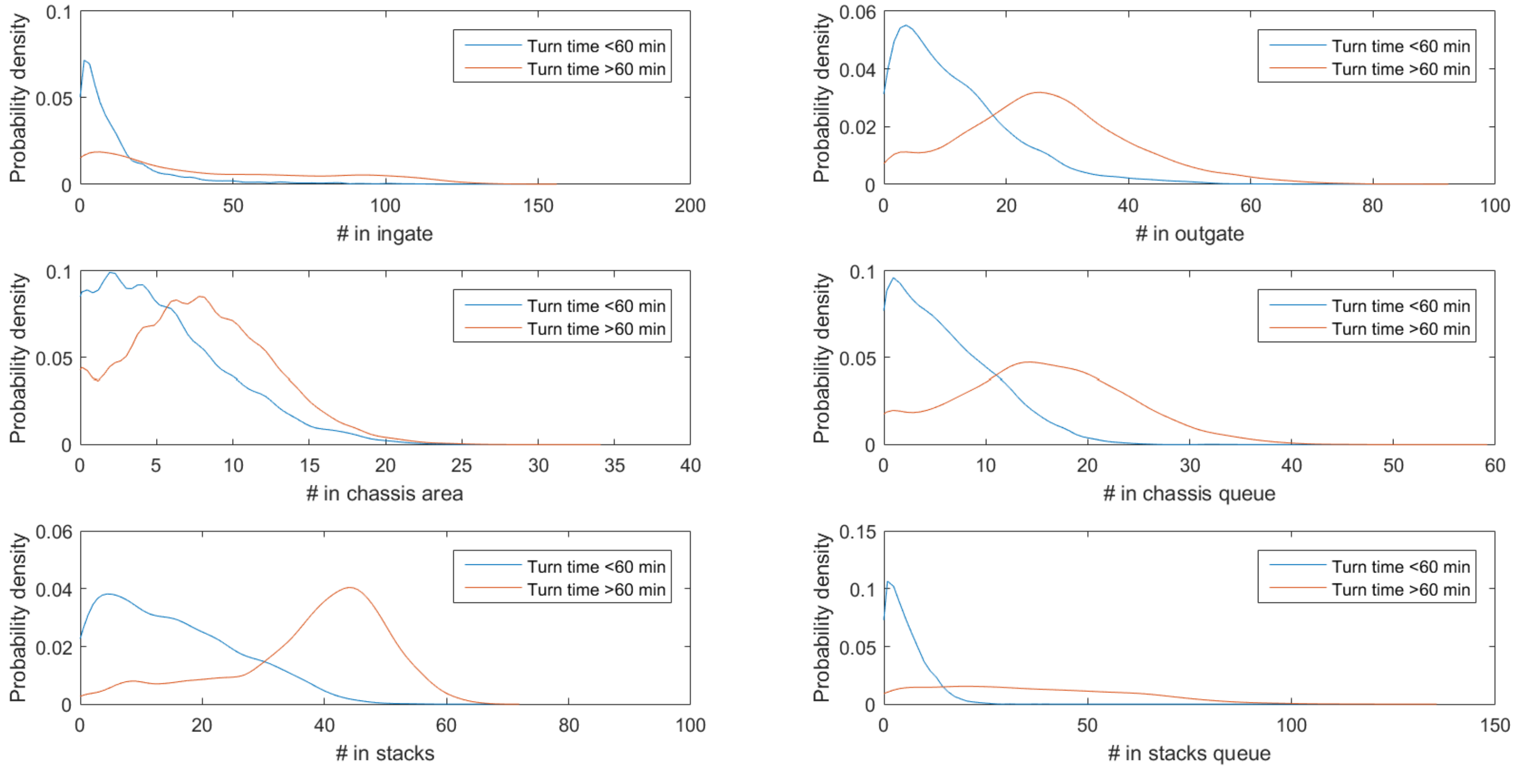

Figure 8-9. Number of trucks in each state, grouped based on traditional turn time.

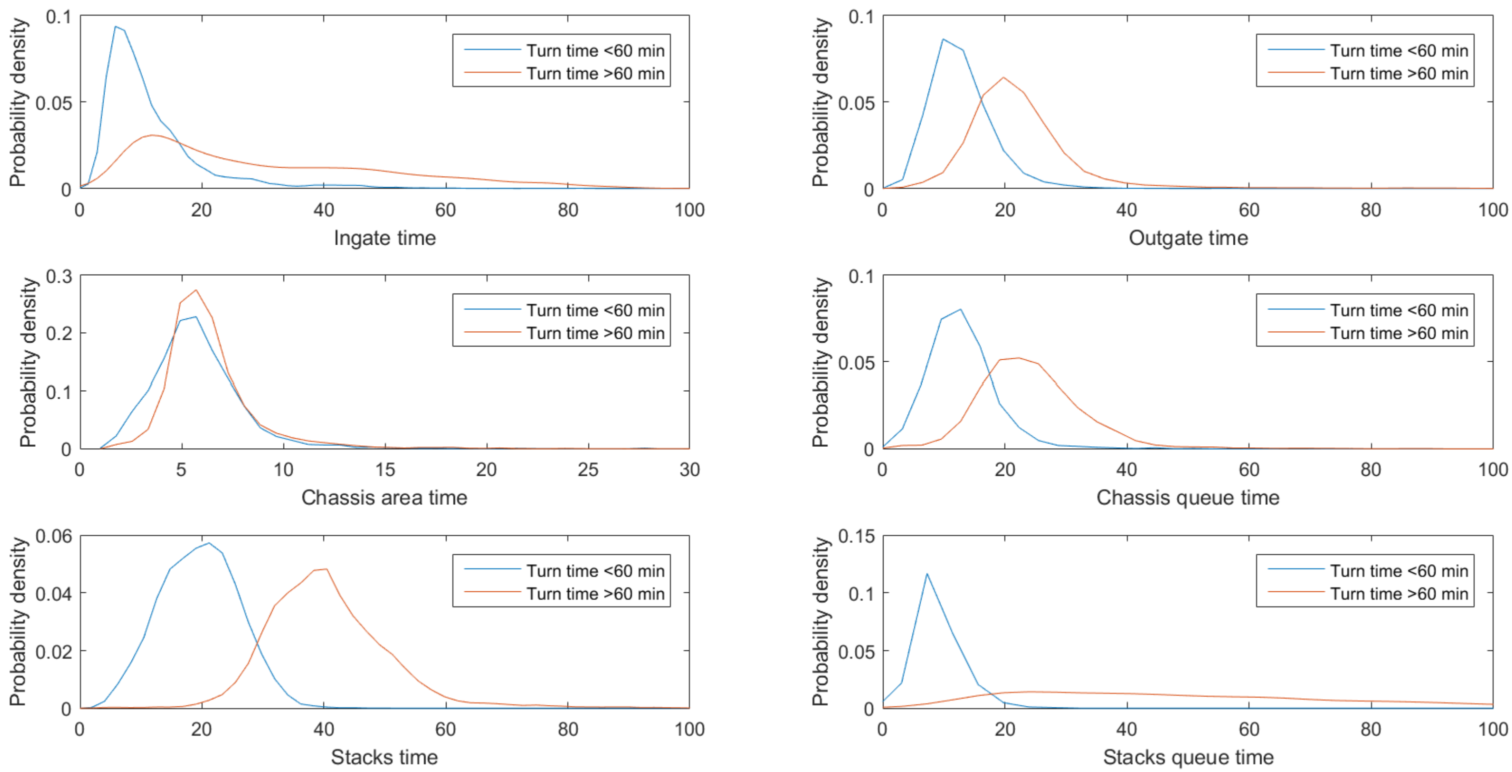

Figure 8-10. Time trucks spend in each state, grouped based on traditional turn time.

The distributions of truck numbers and times for turn times under and over 60 minutes can be formally compared using the disruption coefficient (Clemons & Bradley, 2000; Condit et al., 2006; Inman & Bradley Jr, 1989; Leydesdorff, 2008). The disruption coefficient for a baseline distributions f_1 and a disrupted distribution f_2, is defined as:

$$D = 1 - \int_{-\infty}^{\infty} \min\big(f_1(t), f_2(t)\big)\, dt \tag{8-1}$$

The disruption coefficient can be interpreted as the long-proportion of instances where the two conditions have different outputs. $D = 0$ implies that the distributions are identical whereas $D = 1$ means there is no overlap. Similar measures have been used to compare income distributions of demographic groups (Clemons & Bradley, 2000), eco-diversity (Condit et al., 2006), author co-citation analysis (Leydesdorff, 2008), and in other applications.

The disruption coefficients for comparison of turn times under and over 60 minutes are described in Table 8-2. The chassis area has the lowest disruption for both the number in the state and the time spent there. The stacks queue is the state most disrupted when turn times are over 60 minutes. With the exception of the chassis area, the time in state is more disrupted than the number of trucks in the state.

Table 8-3. Disruption between state probability distributions for turn times under and over 60 minutes. All coefficients are significant at the 0.05 confidence level, evaluated with the Kolmogorov-Smirnov test.

	Number in state disruption	Time in state disruption
Ingate	0.45	0.50
Outgate	0.51	0.58
Chassis area	0.25	0.15
Chassis area queue	0.53	0.65
Stacks	0.64	0.84
Stacks queue	0.73	0.87

Trucks entering the terminal can either go to the *stacks* to receive or deliver a container, or to the *chassis area* to receive or deliver a chassis, have a chassis inspection or repair. Trucks can perform multiple transactions in each state in a single visit, e.g. deliver a twenty-foot container to the *stacks*, go to the *chassis area* to get a forty-foot chassis, and then back to the *stacks* to receive a forty-foot container. In this case each transaction is recorded. The order in which transactions are performed is decided by the driver. Sometimes, like in the example before, there is a natural order, while other times the driver can decide where to start. Table 8-3 illustrates the transitions between states, modeled as a Markov chain. It is possible to go straight from *ingate* to *outgate*, implying that neither the *stacks* nor the *chassis area* was visited. The reasons for such behavior are several and are addressed in the discussions in Chapter 9 on uncertainty in modeling. A majority of trucks entering through the *ingate* to the *stacks*, while the majority of trucks at the *stacks* or in the *chassis area* head for the *outgate*. Movements between the *chassis area* and *stacks* are not symmetrical as a higher proportion of trucks at the *stacks* go to the *chassis area* than trucks at the *chassis area* move to the *stacks*.

Table 8-4. Transition proportions, e.g. 17% of trucks entering through the *ingate* went first to the *chassis area*, 70% went to the *stacks*, and 13% neither visited the *chassis area* nor *stacks*.

	Ingate	***Chassis area***	***Stacks***	***Outgate***
Ingate	0	0.17	0.70	0.13
Chassis area	0	0.03	0.24	0.73
Stacks	0	0.37	0.12	0.51
Outgate	0	0	0	1

Summary

This chapter discusses disruption analytics for truck operations at a container port. It identifies states of operations that have the potential to create bottlenecks when stressed. It compares and contrasts operations when truck turntimes, the time it takes for a truck to complete a visit to the terminal, are under and over 60 minutes. It finds that the stacks and stacks queue states are most disrupted when turntimes are over 60 minutes, indicating that promoting efficiency in those states is key to lowering overall turntimes.

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Chapter 9

Discussion

Overview

This chapter provides a discussion of various challenges, limitations, implementations, extensions, and other topics related to the theory, methodology, and demonstration of this dissertation.

Model testing and evaluation

This task describes validation frameworks for systems modeling and risk analysis. Validation and verification are important steps before models are implemented for real-world applications. Validation has been described as "building the right system" and verification answers "whether the system is built right" (Balci, 1994). Validity of simulation studies is typically tested by comparing results to real-world outcomes with the same input specifications. When the study purpose is to evaluate future, often unprecedented, scenarios comparison with historical data becomes problematic. Balci (1995) discusses 15 principles of simulation validation, verification, and testing. The third principle states that "a simulation model is built with respect to the study objectives and its credibility is judged with respect to those objectives." Macal (2005) acknowledges the difficulty in validating models where historical data to compare to does not exist. They provide pathways to validation in that case:

- Explore extreme and strategic cases
- Use models are exploratory e-laboratories (e.g. for rapid prototyping)
- Use multiple models
- Maximally diverse model ensembles
- Use subject matter experts for evaluation and participatory simulation

Thus by accounting for uncertainties ranging from stochasticity of inputs to exploratory scenarios to accounting for recognized uncertainties, the methodology proposed is partially self-validated. Close collaboration with subject matter experts on modeling constraints, input data quality, and system objectives further increase they credibility of the method.

For a more quantitative validation and verification approach, sensitivity analysis has been defined as "the study of the relative importance of different factors on the model output" (Saltelli, 2017). Saltelli et al. (2004) describe 7 steps of sensitivity analysis applied to risk analysis and decision support:

- Establish the goal of the sensitivity analysis.
- Decide what input factors to include.
- Choose a distribution for each input factor.
- Choose a sensitivity analysis method.
- Generate input sample.
- Evaluate model with input sample.
- Analyze model output and draw conclusions, iterate if deemed necessary.

Frey and Patil (2002) give an overview of ten methods for sensitivity analysis and categorize them as mathematical, statistical, or graphical. Popular methods include Monte Carlo simulation (Greenland, 2001), regression analysis (Homma & Saltelli, 1996), and scatter plot examination (Frey & Patil, 2002).

Uncertainty in modeling

There is a variety of methods for handling uncertainty in the modeling of engineering systems (Chatzi, Papadimitriou, & Beck, 2016). Uncertainty has been specifically accounted for in risk and decision models for infrastructure climate adaption (Espinet, Schweikert, & Chinowsky, 2015; Hamilton, Lambert, & Valverde, 2015), asset management of canal systems (Elcheikh & Burrow, 2016), watershed management (Liu et al., 2007), vessel berth scheduling (Y. Xu et al., 2012), and highway access safety (J. Xu, Lambert, & Tucker, 2014). In many cases expert elicitation (Ayyub, 2001; Hickey & Davis, 2003; Kadane & Wolfson, 1998) is required to assess and evaluate uncertainties. Morgan et al. (2000) and Haimes (2015) propose classification schemes for different types of uncertainty.

Following the chapter on truck operations, this section identifies 8 layers of uncertainty encountered that are summarized in Table 9-1. The layers arise in the analysis of a variety of advanced logistics systems. Challenges are caused by different standards between databases, different scope of data collection for similar systems (two terminals with different data management systems), and other issues where the data collected is accurate but scope or format is inadequate to fulfil requirements. Bad data, e.g., where values are recorded wrong into a data base are another source of uncertainty. This can results in infeasible results, such as a truck having a negative turn time. Finally, the performance metrics, and their user interface and visualization, should address the goals and objectives of the analysis and stakeholders should be able to easily interpret and understand the outcomes.

Table 9-1. Summary of how uncertainty layers were identified in the analysis of advanced logistics systems.

Uncertainty layer	Sample of observations
Data gaps	Not all activities performed during a truck visit are recorded in a database
Comparability across terminals	Different data collection systems can result in incomparability
Comparability within terminal	Lack of identification to link instances in different databases to each other
Data accuracy	Data is recorded incorrectly, either due to technical faults or entering errors
Data completeness	Data fields are only partially recorded, leaving analysts to make inappropriate assumptions
Deficient metrics	Performance metrics are chosen for their convenience rather than representation of system goals
Choosing new metrics	Metrics need to represent goals of system and be meaningful and easily interpreted
User interfaces	Necessary performance information must be presented without overwhelming user with a complicated interface

Data gaps

The uncertainty layer addresses that data is not recorded fully for all activities. For the VIG container terminal, time stamps are recorded when 1a) a truck enters the *ingate* queue, 1b) they enter terminal through the *ingate*, 2a) they are admitted to a spot by the *stacks*, 2b) transaction finishes at the *stacks*, 3a) they enter *chassis area*, 3b) they leaving *chassis area*, and 4) the leave through the *outgate*. In the analysis presented, the *ingate*, *stacks* and *chassis area* states can be accurately defined by these time stamps. The remaining states, *stacks queue*, *chassis queue*, and *outgate*, are estimated by interpolating between the truck leaving one from a transaction and starting another. Thus the term *queue* is not necessarily accurate. For example, while a driver is in the state *stacks queue*, they might be parked for a meal break or having an issue resolved.

Driver's assistance is a state that is not recorded a database. When there is a complication with a transaction, such as mistakes on paperwork, containers are damaged or dislocated, the truck driver visits driver's assistance to have the complication resolved. Experience has taught that a visit to driver's assistance can take anywhere from a few minutes to a couple of hours. At VIG, the driver's assistance building is located outside the gates so the driver has to exit the terminal and re-enter following a visit. Thus it creates an additional record for the same requested transactions. As illustrated in Table 3, 13% of trucks go from *ingate* to *outgate* without visiting *stacks* and *chassis area*. A possible explanation is that some of these trucks have trouble with their transactions, have to go to *driver assistance* and subsequently re-enter the terminal. Since a visit to *driver assistance* is not recorded in a database, it is excluded from any analysis and can affect performance measures.

Comparability across terminals

The Port of Virginia operates three container terminals. In addition to VIG, there are Norfolk International Terminal (NIT) and Portsmouth Marine Terminal (PMT). The latter two are currently not automated to the same extent as VIG and therefore their operations are slightly different. Furthermore, data (specifically time stamps) collected for truck visits is different. Figure 9-1 illustrates the differences in time stamp collection between VIG and NIT. Due to different layouts and operations systems, *chassis area* data is not collected in the same manner. Rather than recording enter and exit times, the gate processing times are recorded. Once the trucks enter the *chassis area*, no further time stamps are recorded. The gate processing times are also recorded for *ingate* and *outgate*. This provides more detail about gate transactions than at VIG, where only the time a truck is finished processing is recorded. An implication of this is that at NIT it is possible to distinguish a long *ingate* (or *outgate*) queue due to traffic from a long queue dues to slow processing by gate operators.

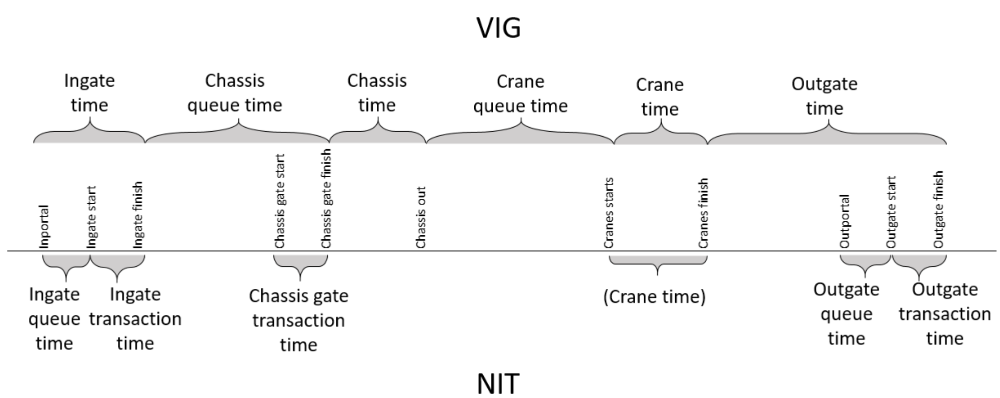

Figure 9-1. Comparison of collected time stamps and analyzed states at two terminals of the Port of Virginia, the VIG and NIT.

Comparability within terminal

Revisiting Figure 11, there is no information about *stacks* or *chassis queue* times at NIT. This is due to incompatibility between databases for truck visits at the terminal. Two databases contain information about truck visits. One has information collected at the *ingate*, *outgate* and chassis gates. The other has information from the *stacks*. A unique identifier for each truck visit links the two databases at VIG. However, at NIT the truck visit identifier is not the same for the two databases and therefore it is not possible to link stack transactions to gate transactions. Furthermore, since *chassis area* and *stacks* transaction can be performed in any order, the *chassis queue* state cannot be extracted from the data and state transitions cannot be computed.

Data accuracy

Time stamps are recorded in various formats in each database. Most are recorded correctly and do not cause any problems but however there are instances where recorded time stamps are not accurate. As an example, of roughly 300,000 truck visits to VIG during the study period, about 30,000 (10%) have time stamps such that when calculating turn times, the turn time is either negative, over twelve hours, or either *ingate* or *outgate* time are missing. When computing average turn times and state transitions, these instances can be filtered out since it is obvious that a truck cannot spend negative time at the terminal or leave without entering. However, there are issues with any filtering approach. The most important one is that even though data collected on these visits was bad, it was still an actual visit with the port personnel providing services to the driver. The experience of these drivers contribute to the terminals overall customer experience. The reasons for bad data can be various and difficult to track. In a worst case scenario, the bad data is due to anomalies in the visit, such as trouble with paperwork or cargo and a need for drivers to seek assistance. In that case, these 10% of visits might have a disproportionally high effect on overall customer experience as drivers tend to weigh a long and complex visit heavier than a shorter business-as-usual visit. Still these visits are not included in performance measurements meant to represent the efficiency of operations, such as daily average turn time.

Data completeness

The data utilized to analyze factors contributing to length of turn times was not exclusively collected for this purpose. Some of the data were in the past collected for a purpose but have since become obsolete. A field for the information still exists in the database and is sometimes filled out and sometimes not, based on whoever is entering the information. When an analyst who is not necessarily in direct communication with the persons entering the data this might create confusion when data is treated as it was accurate while it is in fact only partially complete. This issue has been addressed by other researchers in the field of risk and uncertainty (Connelly et al. 2016).

Deficient metrics

As discussed before, the daily average turn time is the main performance metric used for port drayage operations. The metric is good to exemplify daily throughput but falls short on being a comprehensive representation of terminal efficiency. There are two main perspectives to consider when measuring truck operations at marine terminals: the perspective of the terminal operator and the perspective of the truck driver. Both benefit from a fast throughput and as few trouble visits as possible. A good performance metric should represent the goals and objective of the system it represents (Gibson et al., 2016). Using the average of turn times presents several considerations. The turn times are not symmetrically distributed around the average since they are bounded below by zero but can take values several hours longer than the average of around 60 minutes. This means that the median, which can be thought to represent a typical visit, is lower than the average. More concerning is that it is possible that the satisfaction of drivers is not driven by a typical visit but rather an atypical visit. The average does not distinguish between a hypothetical day where all trucks have turn times close to the average and one where half of trucks have a very short turn time and the other half have a very long one. If a goal of operations is to improve customer satisfaction, the performance metrics need to address these longest turn times.

Choosing new metrics

The uncertainty incurred by using average as a performance metric can be partially addressed by adding another metric or metrics and considering the combinations of performance metrics. A metric that is less sensitive to large outliers while still addressing the goal of keeping turn times under 60 minutes is the proportion of turn times under a threshold value. The benefit of proportion under/over a threshold value is that it gives a clearer indication of how many visits meet the criterion for what could be considered an efficient visit, and complementary, how many visits did not meet the criterion. On the other hand, if the goal is to portray a typical visit, the median could be a better option. Another downside is that when more performance metrics are added, ranking based on the metrics gets more complicated and trade-offs between metric might be necessary to establish a preference order.

User interface

The performance metrics discussed so far, average, proportion under/over a threshold, and median, are limited by their dimensionality as they aggregate data into a single number. Various forms of visualization can provide more complete insight into truck turn times. Figure 12 illustrates a sample interface for turn time efficiency. The interface shows three numeric metrics: the average turn time, the proportion of truck visits with turn times under 60 minutes, and the proportion of trucks with turn times under 75 minutes. The 60 minute threshold is chosen to represent the goal of turn times being less than an hour. The 75 minute threshold is chosen to account for turn times that do not meet the 60 minute threshold but might still not be considered excessively long, thus eliminating some of the ambiguity in the choice of thresholds. In addition the interface has two graphics. The first is a histogram showing the distribution of turn times and the second shows the average turn time per hour. For the sample day in Figure 9-2, the histogram reveals that the most populated bin was 24-36 minutes, which is lower than the daily average of 39 minutes. 84% of visits were under an hour and 93% under 75 minutes. There are however a few very long turn times and details on these visits should be investigated. The second graphic shows that turn times were fairly stable from the morning until mid-afternoon when decreasing until gates close at 18:00.

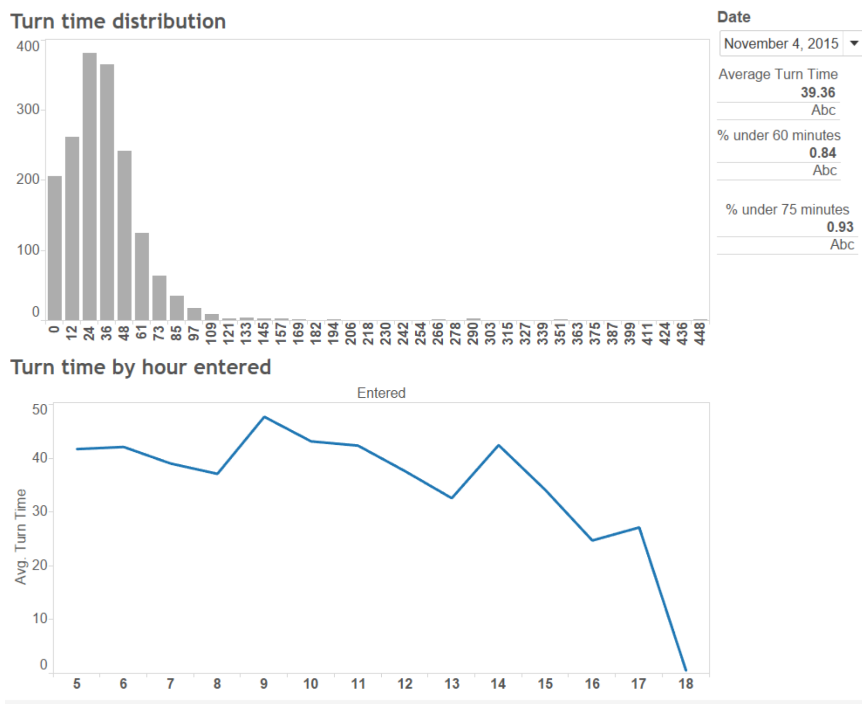

Figure 9-2. Sample interface for truck turn time, displaying the distribution of the length of turn times, time series of average turn time by hour, as well as three metrics: daily average turn time, proportion of turn times under 60 minutes and proportion of turn times under 75 minutes.

Boundaries of analysis

The methodology presented in the dissertation is flexible and can be fitted to a variety of scheduling problems. However, there are instances when the boundaries of applicability are reached. When implementing the methods it is important to be aware of limitations that can mislead the results and their implications.

The disruption coefficient, as defined in Chapter 3, should not be viewed in isolation and must always be viewed in the context of other system characteristics. The strength of the disruption coefficient is that is quantifies the lack of overlap of some performance between two scenarios. The philosophical motivation for it is that "normal" performance is characterizes by a distribution rather than an expected value and a change in the distribution is more impactful to system stakeholders than variations within the baseline distribution. However, a limitation of the coefficient is that its upper bounds at a value of 1 is defined as no overlap between the two distributions or sets under consideration. Thus, once the disruption reaches 1, the coefficient does not extends to further disruptions. Figure 9-3 demonstrates an example with a baseline performance and two disrupted performances. The disruption coefficient for both is 1 but as is evident by the graph "Disruption 2" can be descried as "more disrupted" by the deviation in performance. Thus it important, when using the methods of this dissertation to inform decisions and policy, that multiple criteria beyond the disruption coefficient are considered. This is exemplified in the demonstrations where the absolute values of performance measures are reported as well as the disruption coefficient.

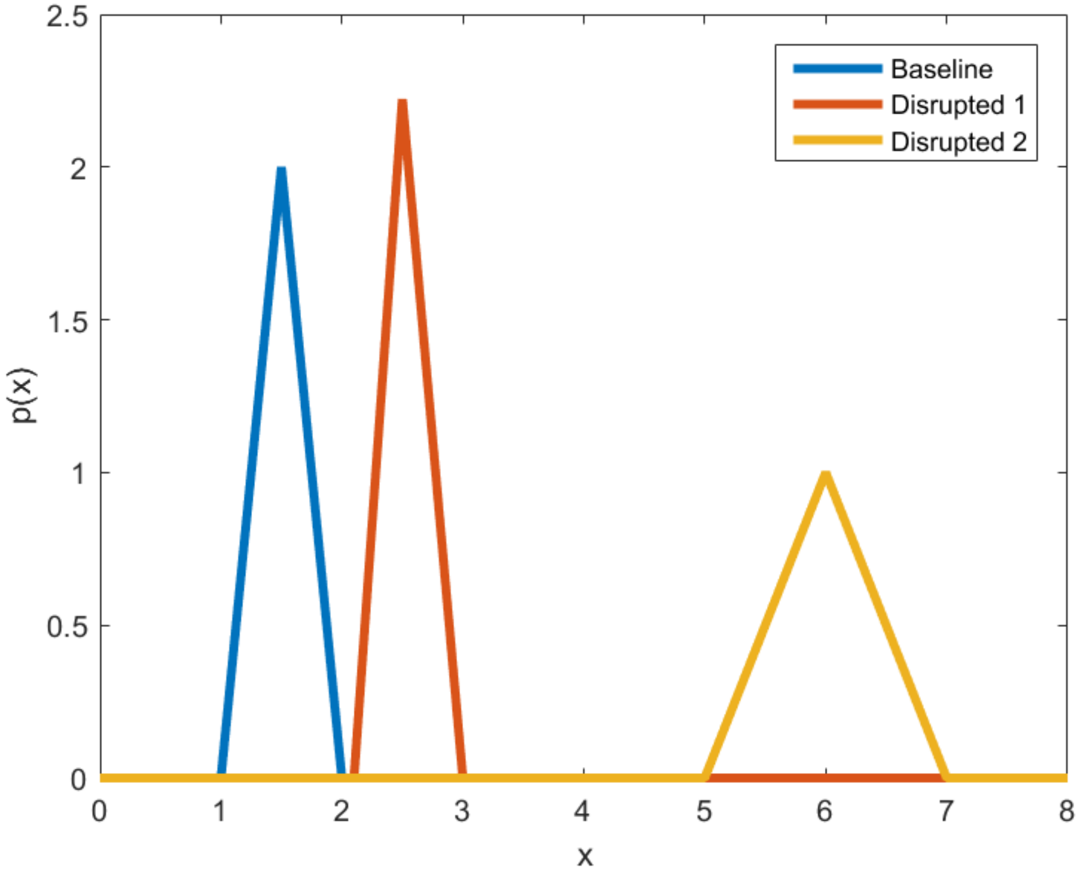

Figure 9-3. Illustrative example of limitations of disruption coefficient when disruption reaches a value of 1.

Another limitation arises, in the vessel berth scheduling, when constraints are put on maximum delay of vessels. It is possible to have a set of arrivals such that it is not possible to berth all vessels within the time frame constrained by the maximum delay between arrivals and time of berthing. In that case, the optimization problem is infeasible. Thus, for each scenario run (each Monte Carlo simulation run) there are infeasible instances. When there is no maximum delay, rather a penalty cost for late berthing, infeasible solutions can be caused by vessels arriving too late to be finished handling within the time frame of the optimization. Most often, this is a small proportion but can be thought of as an indication of the confidence that can be placed in the results, or how frequently the approach fails to tackle a situation that can arise in the real world.

Table 9-2 contains the proportions of feasible instances for the 36 disruptions analyzed in chapter 5 about operations disruptions. In general there is a higher proportion of instances in disruptions when the container volumes are disrupted.

In addition, running a large number of simulations can be expensive in terms of computing resources. Efficient algorithms can drastically reduce the time it takes to solve an instance of a mixed-integer linear program, however it is an NP-complete problem and can in the worst case scenario have an exponential time complexity. With limited computing resources it may therefore be necessary to put use an approximation of the optimal solution, limit running time of each instance, or make other tradeoffs between accuracy and efficiency.

Table 9-2. Proportion of feasible instances in the 36 operations disruptions discussed in chapter 5.

Disruption	Proportion of infeasible instances
0	***0.96***
1	0.97
2	0.97
3	0.96
4	0.96
5	0.86
6	0.78
7	0.82
8	0.77
9	0.74
10	0.73
11	0.76
12	0.78
13	0.96
14	0.97
15	0.96
16	0.97
17	0.97
18	0.96
20	0.97
21	0.97
22	0.97
23	0.96
24	0.97
25	0.82
26	0.86
27	0.96
28	0.96
29	0.91
30	0.96
31	0.95
32	0.89
33	0.94
34	0.90
35	0.83
36	0.86

The data inputs to the vessel berth scheduling discussed in Chapters 4-8 assume simple relationships between some key variables. For example does handling time increase linearly with number of containers handled, the per-unit-cost of handling is invariant to number of containers handled (both by vessel and by terminal), and vessel arrival delays are independent between vessels. In reality, it is possible that once the number of containers pass a critical point, operations become slower and marginally more expensive. Vessel arrival delays are likely to be interdependent as conditions such as weather or slowdowns in previous ports affect multiple consecutive vessels. Future work should statistically explore the interdependencies between input variables and how that impacts the methodology.

The appropriateness of input data is fundamental to the success of the methodologies of this dissertation. An element of the methodology is to use historical data as a baseline for future planning before adding disruptions that may be supported by subjective projections and anticipated policies. Deciding the data to use to fit the distributions of input variables requires some consideration. On one hand, if little data is available, confidence in the fit might be an issue. Hypothesis testing for linear regression can be helpful deciding whether the information contained in the data is enough to warrant the correlation of variables such as handling time and number of containers. On the other hand, if data is available for a long period into the past, the applicability of older data could pose challenges. For example, if a port updates facilities, buys more efficient cranes, adds a terminal, or other drastic changes, it might be questionable whether data from the period before that update should be included. Thus selecting the appropriate data for the baseline model is a non-trivial problem. Bayesian statistics offer methods that can help the selection of appropriate data. Using Bayes theorem, new information collected can be used to update the prior input distributions.

Potential benefits of application

The methodology is developed to be applied in enterprise scheduling, most specifically vessel berth scheduling at container ports. It leverages the large amounts of operations data collected for various purposes, with techniques of applied mathematics, statistics, operations research, and risk analysis, all guided by holistic systems engineering principles. The models developed are meant to be realistic, even though they do not perfectly describe reality, so they can be used to make meaningful, data-driven decisions.

The baseline vessel berth schedule model outlined in Chapter 4, and further developed in Chapters 5-7, is based on a sample vessel schedule at the Port of Virginia. A goal is to improve that sample schedule in terms of key performance, such as operations cost, delays, and others. Figure 9-3 illustrates the comparison between model-informed schedule options from Chapter 7 and the sample schedule, in terms of mean operations cost and mean delays. The cost and delays are evaluated in a Monte Carlo simulation over random vessel arrival times, handling times and number of containers. As the figure demonstrates, the cost of the sample schedule is higher than for all the model-informed schedule option, however the sample schedule performs close to the best options in terms of delays.

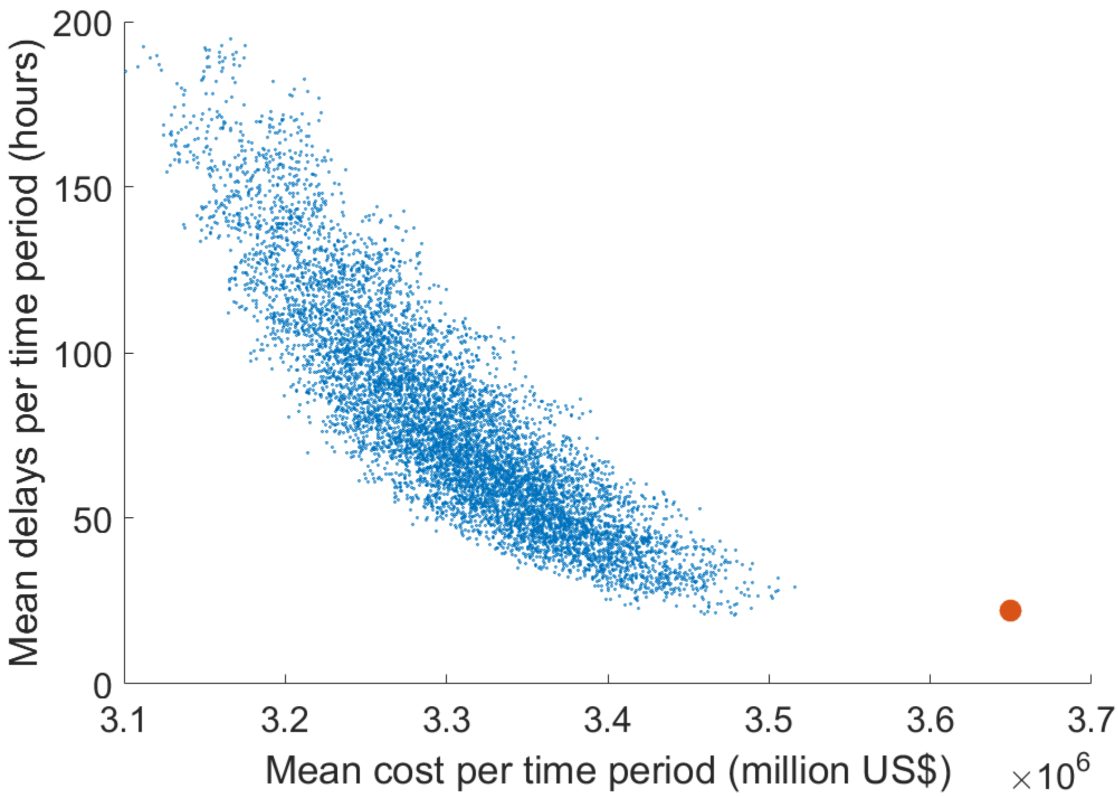

Figure 9-4. Comparison of model-informed schedule options (blue) to performance of sample schedule (orange).

Figure 9-5 and Figure 9-6 shows another perspective than Figure 9-4. Here, only schedule options with a mean delay shorter than the sample schedule are shown. This reduces the number of schedule options from 8305 to 7. The remaining schedule options have a mean cost of $150,000-$200,000 per week lower than the sample schedule. In other words, the results from the modeling have the potential to reduce operations cost at the organization by up to $200,000 per week (~$10 million annually) while not compromising on another main objective, vessel delays. Figure 9-5 shows the performance of 7 schedule options and the sample schedule with ranges showing the maximum and minimum as well as the mean of the operational cost and delay measures. The delay ranges are similar for all schedule options and the sample schedule. The cost ranges have significant overlap, however the ranges for the 7 modeled schedule options are shifted towards lower cost. Figure 9-6 shows the distributions for the operational cost of the sample schedule and the 7 schedule options. The sample schedule distribution is shifted relatively towards higher cost. It is partially disrupted with the disruption coefficient of the schedule options around 0.5. The interpretation of those values mean that in half of weeks in the long run operations according to one of the schedule options would perform better in cost than with the sample schedule.

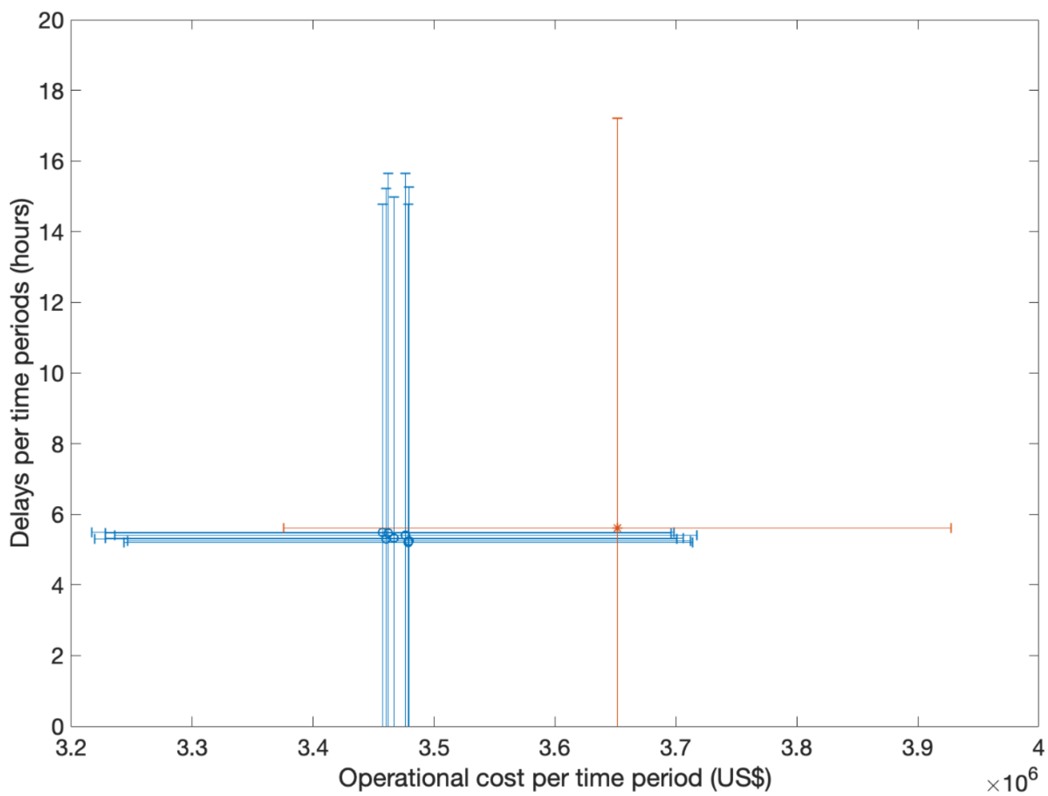

Figure 9-5. Comparison of model-informed schedule options (blue) to performance of sample schedule (orange) when schedule options are filtered to those with less delays than the sample.

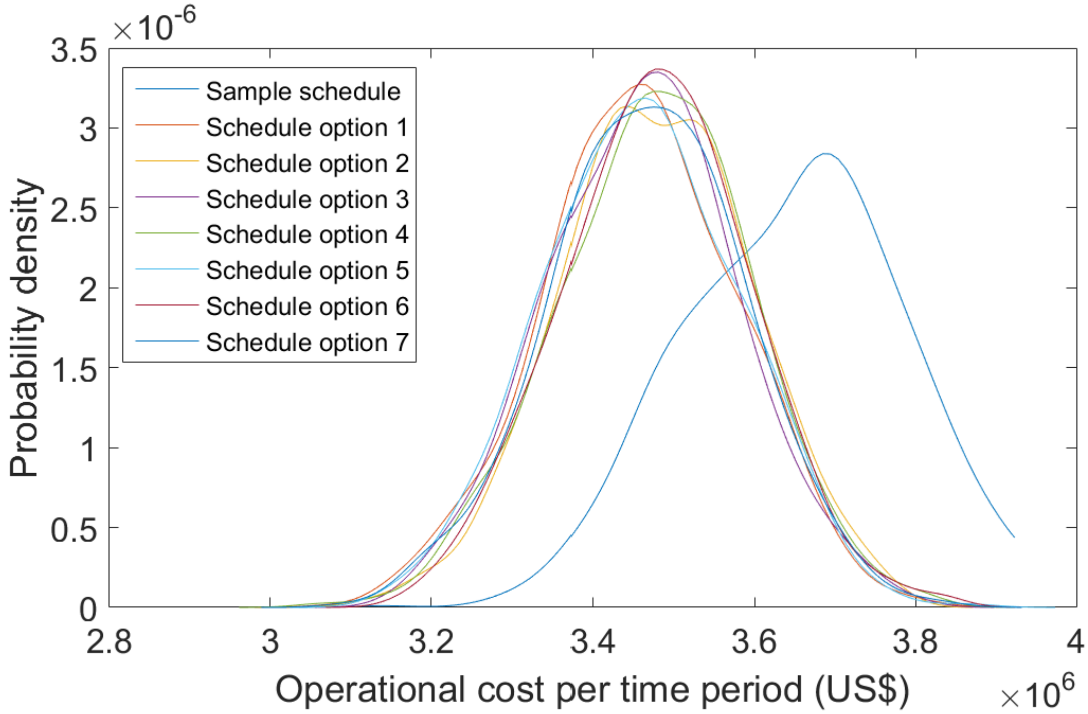

Figure 9-6. Cost distributions of sample schedule and 7 schedule options, filtered so that schedule options have lower mean delay than sample schedule.

The savings demonstrated above could be transformative for any port, or other organization, if the schedule options can be implemented. However, future research should focus on including a more complete set of requirements and costs. For instance, most vessels calling at the port are parts of larger alliances that share some services, routing, and resources (similar to airline codeshares). One significant operations consideration not included in the scheduling model is cost associated with empty containers. Alliances store empty containers at port terminals and the port operators charge a fee for this service. The empties are then sometimes loaded on vessels to be moved to another port where there is demand for empty containers. In general, containers can go on any vessel of the particular alliance. Thus it is desirable to schedule multiple or all vessels of the same alliance at the same terminal. Otherwise the port has to hire a truck to move empties between terminals which decreases the profit from storage of empty containers. Including the costs and revenues from empty container storage and handling should be a major direction of future research.

The methodology and modeling approach of the dissertation is flexible and can be implemented for a variety of processes. However, there is great potential within container port operations. In addition to the Port of Virginia there are over 20 container ports in the United States, on the East, West, and Gulf Coasts. Table 9-3 summarizes volume and the number of container terminals at the busiest container ports in the United States (American Association of Port Authorities, 2017). The Port of Virginia ranks 6th in terms of volume. Most ports, with the exception of Port of Savannah have more than one container terminal and face the same challenges of scheduling vessels to particular terminals that have different specifications, capacities, and costs. The methods of the dissertation could be of interest to operators at each of these ports, as well as other container ports worldwide.

Table 9-3. Top US container ports by volume handled and number of container terminals within port (American Association of Port Authorities, 2017).

Port	Number of container terminals	2017 volume (million TEUs)	Source of terminal information
Port of Los Angeles	8	8.9	(Port of Los Angeles, 2018)
Port of Long Beach	6	6.8	(Port of Long Beach, 2018)
Port of NY-NJ	6	6.7	(Port of New York and New Jersey, 2019)
Port of Savannah	1	4.0	(Georgia Ports, 2015)
Port of Seattle/Tacoma	8	3.7	(Northwest Seaport Alliance, 2018)
Port of Virginia	3	2.8	(Port of Virginia, 2019)
Port of Houston	2	2.4	(Port Houston, 2019)
Port of Oakland	3	2.4	(Oakland Seaport, 2019)
Port of Charleston	2	2.2	(South Carolina Ports, 2019)

Summary

This chapter has described several topics related to the dissertation. Particularly, model testing and evaluation, uncertainty in modeling, and boundaries of modeling are discussed, as well as potential benefits of applying the methods of the dissertation to container port scheduling.

Chapter 10

Summary and conclusion

Overview

This chapter summarizes the research contributions of the dissertation, discusses publications and presentations relevant to the effort, and proposes avenues for future work.

Review of research contributions

The dual control problem, balancing the knowledge acquisition and driving system performance, was introduced in the motivation for this research effort. The modeling framework developed in this dissertation supports the underlying philosophy of dual control or the exploitation/exploration tradeoff in machine learning. Throughout the dissertation, efforts have focused on either i) collecting information or learning about how the system schedules are impacted by various disruptions, or ii) devising strategies to make the best schedules possible. In other words, taken together the framework aims to maximize the utility of schedules (e.g. minimizing cost), under current conditions and under a variety of emergent and future conditions. This is achieved by exploring multiple objectives (in particular Chapter 6), multiple inputs and parameters (in particular Chapter 5), as well as leveraging best current information to make robust decisions (in particular Chapter 7). Real-world systems, such as a container port, are complex so describing them with single equations or models in insufficient. Thus, the framework should be viewed as a human in the loop decision aiding process, where the models and results of analyses inform and are used to formulate recommendations in conjunction with system stakeholders and subject matter experts.

This dissertation makes contributions to the theory, methods, and applications of systems engineering and risk analysis. The contributions are illustrated throughout the dissertation and summarized as follows:

- *Contribution 1: Modeling framework for scheduling with stochastic model elements.*

The framework is introduced in Chapter 3 and further developed and discussed throughout the dissertations. Representing and analyzing systems with the schedules that drive their functions extends the systems engineering paradigm and addresses underlying objectives and interconnectedness among system elements. The framework combines a mixed-integer linear model and Monte Carlo simulation to assign system elements to locations and times given a set of requirements. The framework extends the theory and methods of the generalized assignment model by including random input and decision variables. Most relevant publications: Thorisson et al. 2019a, Thorisson et al. 2019b.

- *Contribution 2: Quantification of schedule disruptions for risk comparisons.*

Development of measures that quantify disruptions of both schedule assignments and schedule performance. The measures have a theoretical foundation in probability, set theory, information theory, and others. They contribute to theory by quantifying the level (fully disrupted, partially disrupted, not disrupted) of disruption of probabilistic schedules and performances. The measures are defined in Chapter 3 and demonstrated and discussed throughout the dissertation. Most relevant publications: Thorisson et al. 2019a, Thorisson et al. 2018, Thorisson et al. 2017.

- *Contribution 3: Model-informed operational disruption analysis.*

Applying the modeling framework to evaluate impacts of operational disruptions to scheduling. The operations disruption analysis is discussed in Chapter 5. The analysis applies risk analysis principles to scheduling framework to collect information about a marine container port when subjected to a set of various emergent and future conditions. Most relevant publication: Thorisson et al. 2019a.

- *Contribution 4: Model-informed tradeoff analysis of schedules.*

Leveraging modeling framework to balance the multiple objectives of stakeholders, including schedule operational costs, delays, and robustness. The tradeoffs of multiple objectives are discussed in Chapter 6. The chapter contributes to multiple objective decision making by demonstrating how schedules can simultaneously minimize operational cost and delays by accepting lower robustness of the schedule assignments. Most relevant publication in preparation.

- *Contribution 5: Model-informed schedule option development.*

Enumeration, filtering, and evaluation of deterministic schedule options based on the outputs of the modeling framework. The schedule option development is described in Chapter 7. Developing deterministic schedule options can be useful when the time frame of decision making is different than the time frame of the optimization setup. The chapter demonstrates how to exploit the outcomes of the modeling framework in practical situations. Most relevant publication: Thorisson et al. 2019b.

- Contribution 6: Demonstration of modeling framework for a marine container port system.

The framework is implemented for the berthing of container vessels at the Port of Virginia, USA. The demonstration is covered in Chapters 4-8. The results demonstrate that utilizing the modeling framework for vessel berth scheduling at the three container terminals of the port has the potential to lower operational cost of berthing by up to $200,000 per week without adding significantly to the delays incurred by vessels. The cost savings could be even higher if delays are compromised. Analysis of truck operations resulted in a new key performance indicator being added to the weekly operations report presented to the board of the organization.

Publications and presentations

The research described in this dissertation is the culmination of efforts carried out over the years 2014-2019. The results, theoretical, and methodological contributions have been disseminated in archival journal papers, academic conference proceedings, scientific book chapters, and oral and poster presentations at international conferences and workshops. This section lists these publications and presentations. The research appears in publications and conferences of several academic and professional societies, respecting its cross-disciplinary nature, including the IEEE, the Society for Risk Analysis (SRA), the International Council on Systems Engineering (INCOSE), the American Society of Civil Engineers (ASCE), the American Society of Mechanical Engineers (ASME), the European Safety and Reliability Association (ESRA), International Risk

Governance Council (IRGC), the Association of European Operations Research Societies (EURO), International Society on Multiple Criteria Decision Making, and others.

Archival journal publications

Thorisson, H., M. Alsultan, D. Hendrickson, T.L. Polmateer, J.H. Lambert. 2019a. Addressing schedule disruptions in business processes of advanced logistics systems. *Systems Engineering*. 22(1):66-79.

Quenum, A.R., **H. Thorisson**, D. Wu, and J.H. Lambert. 2019. Resilience of business strategy to emergent and future conditions. Early online view in *Journal of Risk Research*.

Thorisson, H., D. Hendrickson, T.L. Polmateer, J.H. Lambert. 2018. Disaggregating uncertainties in operations analysis of intermodal logistics systems. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering.* 5(1).

Almutairi A., **H. Thorisson,** J.P. Wheeler, D.L. Slutzky, J.H. Lambert. 2018. Scenario-based preferences in development of advanced mobile grid services and bidirectional charger network. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering.* 4(2).

Thorisson, H. and J.H. Lambert. 2017. Multi-scale identification of emergent and future conditions along corridors of transportation networks. *Reliability Engineering and System Safety.* 167:255-263.

Thorisson, H., J.H. Lambert, J.J. Cardenas, and I. Linkov. 2017. Resilience analytics with application to power grid in a developing region. *Risk Analysis*. 37(7):1268-1286.

Connelly E.B., **H. Thorisson**, L.J. Valverde, J.H. Lambert. 2016. Asset risk management and resilience for flood control, hydropower and waterways. ASCE-ASME *Journal of Risk and Uncertainty in Engineering Systems. Part A: Civil Engineering.* 2(4).

<u>Conference proceedings:</u>

Thorisson, H., C.A. Pennetti, D.J. Andrews, D. Hendrickson, T.L. Polmateer, J.H. Lambert. 2019b. Systems Modeling and Optimization of Container Ship Berthing with Various Enterprise Risks. To appear in Proceedings of the 2*019 IEEE Systems Conference*. Orlando, FL, USA. 8pp.

Thorisson, H., A. Almutairi, J.P. Wheeler, D.L. Slutzky, J.H. Lambert. 2017. Enterprise management and systems engineering for a mobile power grid. In *Proceedings of the 25th International Conference on Systems Engineering,* Las Vegas, NV, USA. 7 pp.

Collier, Z.A., E.B. Connelly, **H. Thorisson**, and J.H. Lambert. 2016. Resilience of initiatives for shifting management priorities under emergent and future Conditions. In *Proceedings of the 2016 IEEE Systems Conference*, Orlando, FL, USA. 6pp.

Chen, L.X., A.A. Chowdhury, C.M. Loulakis, M.A. Ownes, **H. Thorisson**, E.B. Connelly**,** C.J. Tucker, J.H. Lambert. 2015. Visualization of large data sets for project planning and prioritization on transportation corridors, in *Proceedings of the 2015 IEEE Systems and Information Design Symposium*.

<u>Book chapters</u>

Thorisson, H., F. Baiardi, D.G. Angeler, K. Taveter, A. Vasheasta, P.D. Rowe, W. Piotrowicz, T.L. Polmateer, J.H. Lambert, I. Linkov. Resilience of Critical Infrastructure Systems to

Hybrid Threats with Information Disruption. Summary chapter from NATO Advanced Research Workshop on Security and Resilience of Information Systems Affected by Hybrid Threats to appear in book published by Springer.

Thorisson, H., J.H. Lambert. On the "Influence of Scenarios to Priorities" in risk and security programs. To appear in *Applied Risk Analysis for Guiding Homeland Security Policy and Decisions*. S. Chatterjee, R.T. Brigantic, A.M. Waterworth (eds.). Wiley.

Thorisson, H., J.H. Lambert. 2019. Resilience analytics by separation of enterprise schedules: Applications to infrastructure. In B.D. Trump, M-V. Florin, I. Linkov (Eds). *IRGC resource guide on resilience (vol. 2): Domains of resilience for complex interconnected systems*. Lausanne, CH: EPFL International Risk Governance Council. Available on irgc.epfl.ch and irgc.org.

Thorisson H., J.H. Lambert 2016. Resilience analytics for systems of systems: Literature and resource guide. In Resource Guide on Resilience. Lausanne: EPFL International Risk Governance Center. 8pp. Available on irgc.epfl.ch and irgc.org.

<u>Oral and poster presentations:</u>

Thorisson, H., J.H. Lambert. Disruption theory of enterprise schedules for risk comparisons. To be presented at Society for Risk Analysis World Congress of Risk. Cape Town, South Africa. May 2019.

Thorisson, H., J.H. Lambert. Logistics Schedule Risk Analysis Using Optimization, Simulation, and Similarity Metrics. Presented at Society for Risk Analysis Annual Meeting. New Orleans, LA, USA. December 2018.

Thorisson, H., T.L. Polmateer, and J.H. Lambert 2018. Finding sustainable efficiencies in urban logistics. NSF Workshop on Mathematics for Planet Earth 2013+. University of Georgia. Athens, Georgia. August 5-7, 2018.

Thorisson, H., T.L. Polmateer, J.H. Lambert. Vessel berthing schedules under the influence of emergent and future conditions. Presented at the European Conference on Operations Research. Valencia, Spain. July 2018.

Thorisson, H., J.H. Lambert. Disruptions of emergent and future conditions in advanced logistics systems. Presented at Society for Risk Analysis Annual Meeting. Arlington, VA, USA. December 2017.

Thorisson, H., J.H. Lambert. Influence of risk scenarios in port operations on supply chain resilience. Presented at Society for Risk Analysis Nordic Chapter Meeting. Espoo, Finland. November 2017.

Thorisson, H., J.H. Lambert. Requirements analysis and canonical formulation of a risk, safety, resilience, or security program. Presented at Society for Risk Analysis Annual Meeting. San Diego, CA, USA. December 2016.

Thorisson, H., J.H. Lambert, R.D. Ditmer. Interactions of risk analysis and policy making in infrastructure planning in developing countries. Presented at SRA-Europe Conference 2016. Bath, UK. June 2016.

Thorisson, H., J.H. Lambert. Prioritizing investment risks and opportunities for the power grid in a volatile post-conflict region. Presented at Society for Risk Analysis Annual Meeting. Arlington, VA, USA. December 2015.

Thorisson, H., E.B. Connelly, L.J. Valverde, J.H. Lambert. Risk-informed evaluation of infrastructure project portfolios subject to variable uncertainties. Presented at International Conference on Multiple Criteria Decision Making 2015. Hamburg, Germany, August 2015.

Thorisson, H., E.B. Connelly, L.J. Valverde, J.H. Lambert. Risk-mitigating resource allocation for waterway infrastructure systems. Presented at MPE2013+ Workshop on Natural Disasters. Atlanta, GA, USA. May 2015.

Future work

The efforts presented in this dissertation give rise to several possible avenues of future research. The complexity of the demonstrations leave room for advancements in theory and methodology in the domain of port scheduling and opportunities for further applications are plentiful.

The scheduling approach with optimization and simulation can be nested into an algorithm that iteratively aims at reducing the uncertainty about decision variables (increase the schedule information gain). Weights, derived from assignment probabilities in the previous iteration, could reward particular vessel to terminal assignments and penalize others. This would be balanced by limiting increases in cost (or other objectives) which could also be used as a stopping criterion. This approach has the objective of increasing the schedule information gain, while relaxing the cost minimization and other objectives.

The contribution of the scheduling approach in negotiations could be significant if developed further and integrated with the theory and methods of social and behavioral sciences. The emphasis on exploring the tradeoffs between different operations regimes, perspectives, and filtering of candidate schedule options gives various stakeholders information that can be leveraged to negotiate a schedule that is beneficial to all (Gosavi et al. 2015). This would require a higher level of input from stakeholders and more subjectivity in choosing and ranking preferences, objectives, and other driving elements of the methodology.

The methods have been demonstrated for scheduling at a container port but domains of application are numerous. Some might require additional or a different set of requirements but are based on the foundation laid out in this dissertation. Examples of topics include job scheduling in manufacturing, rostering in hospitals (scheduling shifts for nurses, doctors, and other personnel), budget allocation across public agencies or departments, and many other resource allocation and scheduling applications.

Summary

This chapter has summarized the research contributions, listed publications and presentations related to the effort, and identified areas of future work. Figure 10-1 illustrates the milestones of the dissertation effort which stretches from fall of 2014 until spring of 2019 and includes seven archival journal articles, three articles in conference proceedings, and 14 presentations at conferences.

Figure 10-1. Milestones of dissertation effort.

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Appendix

Create schedule by solving minimization problem

```
function    [results,cost_out,mout,lout,delay_out,berth_plan]    =
solve_proforma(a,h,ncont,ncont_all_modes,lcost)

%% Variable inputs

VIG_max=18000;  % max nr of containers per week at VIG
NIT_max=22000;  % max nr of containers per week at NIT
PMT_min=2000;
cost_max=1003000000; % max cost for berthing all vessels


%% Indices
nn = length(a);    %nr of vessels per time period
i = 1:84;         %time period index
ni = length(i); %nr of time periods
j = 1:9;          %berthing location index
nj = length(j); %nr of berthing locations


%% Decision variables
x = zeros(nn,nj);         %If x(n,j)=1 then vessel n is berthed at
j
m = zeros(nn,1);         %Vessel n is berthed at time m(n)
z = zeros(nn,nn);        %If z(n,m)=1 then vessel m starts after n
finishes
y = zeros(nn,nn);         %If y(n,m)=1 then vessel n is berthed at
a
                         %position indexed lower than m
nx=length(x(:));
```

```
nm=length(m(:));
nz=length(z(:));
ny=length(y(:));
nd=nx+nm+nz+ny;

%% Constraints
lbx=zeros(size(x)); %lower bound of decision variables
ubx=ones(size(x)); %upper bound of decision varibles
lbm=ones(nn,1);
ubm=ni*ones(nn,1);
lbz=zeros(size(z));
ubz=ones(size(z));
lby=zeros(size(y));
uby=ones(size(y));

%% All vessels are berthed
A0=zeros(nn,nd);
b0=ones(nn,1);
for n=1:nn
    Atemp=zeros(nn,nj);
    Atemp(n,:)=1;
    atemp=find(Atemp==1);
    A0(n,atemp(:))=1;
end
```

$$\sum_{p=1}^{P} x_{np} = 1$$

```
%% No overlap in time or space
B=100;

% Overlap in time
A1=zeros(nn*(nn-1),nd);
b1=zeros(nn*(nn-1),1);
count=1;
for n=1:nn
    for k=1:nn
        if n~=k
            A1(count,nx+n)=1;
            A1(count,nx+k)=-1;
            Ztemp=zeros(nn,nn);
            Ztemp(n,k)=1;
            ztemp=find(Ztemp==1);
            A1(count,nx+nm+ztemp)=B;
            b1(count)=B-h(n)-1;
            count=count+1;
        end
    end
end
```

$$t_k + B(1 - z_{nk}) \geq t_n + h_n$$

$$l_k + B(1 - y_{nk}) \geq l_n + 1$$

$$z_{nk} + z_{kn} + y_{nk} + y_{kn} \geq 1$$

```
% Overlap in space
A2=zeros(nn*(nn-1),nd);
b2=(B-1)*ones(nn*(nn-1),1);
count=1;
for n=1:nn
    for k=1:nn
        if n~=k
            for j=1:nj
                Atemp=zeros(nn,nj);
                Atemp(n,j)=j;
                Atemp(k,j)=-j;
                A2(count,1:nn*nj)=A2(count,1:nn*nj)+Atemp(:)';
            end
            Ytemp=zeros(nn,nn);
            Ytemp(n,k)=B;
            A2(count,nx+nm+nz+1:end)=Ytemp(:);
            count=count+1;
        end
    end
end

% Connecting A1 and A2
A3=zeros(nn*(nn-1),nd);
b3=zeros(nn*(nn-1),1);
count=1;
for n=1:nn
    for k=1:nn
        if n~=k
            Ztemp=zeros(nn,nn);
            Ztemp(n,k)=1;
            Ztemp(k,n)=1;
            ztemp=find(Ztemp==1);
            Ytemp=zeros(nn,nn);
            Ytemp(n,k)=1;
            Ytemp(k,n)=1;
            ytemp=find(Ytemp==1);
            A3(count,nx+nm+ztemp(:))=-1;
            A3(count,nx+nm+nz+ytemp(:))=-1;
            b3(count)=-1;
            count=count+1;
        end
    end
end

%% Service doesn't exceed time horizon
A4=zeros(nn,nd);
```

$$t_n + h_n \leq T$$

```
b4=ni*ones(nn,1)-h(:)+1;
for n=1:nn
    A4(n,nx+n)=1;
end

%% Berth after arrival time
A5=zeros(nn,nd);
b5=-a(:);
for n=1:nn
    A5(n,nx+n)=-1;
end
```

$$t_n \geq a_n$$

```
%% Berth within a buffer time from arrival
A6=zeros(nn,nd);
b6=a(:)+3; %name variable, 2 means the ship can be berthed 2 time
periods after arriving
%b6=d(:)-h(:);
for n=1:nn
    A6(n,nx+n)=1;
end
```

$$t_n \leq a_n + \delta$$

```
%% No more than NIT_max containers at NIT
A7=zeros(1,nd);
b7=NIT_max;
Atemp=zeros(nn,nj);
Atemp(:,1)=ncont_all_modes;
Atemp(:,2)=ncont_all_modes;
Atemp(:,3)=ncont_all_modes;
Atemp(:,4)=ncont_all_modes;
A7(1:nx)=Atemp(:);
```

$$\sum_{n=1}^{N}\left(x_{np}\sum\nolimits_{m=1}^{M} TEU_{nm}\right) \leq MAX_p$$

```
%% No more than VIG_max containers at VIG
A8=zeros(1,nd);
b8=VIG_max;
Atemp=zeros(nn,nj);
Atemp(:,5)=ncont_all_modes;
Atemp(:,6)=ncont_all_modes;
A8(1:nx)=Atemp(:);
```

$$\sum_{n=1}^{N}\left(x_{np}\sum\nolimits_{m=1}^{M} TEU_{nm}\right) \leq MAX_p$$

```
%% At least PMT_min containers at PMT
A9=zeros(1,nd);
b9=-PMT_min;
Atemp=zeros(nn,nj);
Atemp(:,7)=-ncont_all_modes;
Atemp(:,8)=-ncont_all_modes;
Atemp(:,9)=-ncont_all_modes;
A9(1:nx)=Atemp(:);
```

$$\sum_{n=1}^{N}\left(x_{np}\sum\nolimits_{m=1}^{M} TEU_{nm}\right) \geq MIN_p$$

```
%% ACL (Vessel 1) must be at PMT
Ax1=zeros(1,nd);
bx1=1;
Atemp=zeros(nn,nj);
Atemp(1,7:9)=1;
Ax1(1,1:nx)=Atemp(:);
```

$$x_{1,3} = 1$$

```
%% EC1 (Vessel 12) and EC3 (Vessel 13) at same terminal
Ay1=zeros(3,nd);
by1=zeros(3,1);
%NIT
Atemp=zeros(nn,nj);
Atemp(12,1:4)=1;
Atemp(13,1:4)=-1;
Ay1(1,1:nx)=Atemp(:);
%VIG
Atemp=zeros(nn,nj);
Atemp(12,5:6)=1;
Atemp(13,5:6)=-1;
Ay1(2,1:nx)=Atemp(:);
%PMT
Atemp=zeros(nn,nj);
Atemp(12,7:9)=1;
Atemp(13,7:9)=-1;
Ay1(3,1:nx)=Atemp(:);
```

$$x_{12,p} = x_{13}, p$$

$$\min_{n,p} c_{np}^T x_{np} = C$$

```
%% Objective
cost=zeros(nn,nj);
for n=1:nn
    for j=1:nj
        cost(n,j)=sum(ncont(:,n).*lcost(:,j));
    end
end

%delay_cost=20000.*ones(nm,1);

%% Constraint: cost is less than cost_max
% A11=zeros(1,nd);
% b11=cost_max;
% A11(1:nx)=cost;


%% Solve problem
f=[cost(:); zeros(nm+nz+ny,1)];
```

```
A=[A1; A2; A3; A4; A5; A6; A7; A8; A9];
b=[b1; b2; b3; b4; b5; b6; b7; b8; b9];
Aeq=[A0; Ax1];
beq=[b0; bx1];
%Aeq=[A0; Ax1; Ay1; Ay2; Ay3; Ay6; Ay7; Ay8];
%beq=[b0; bx1; by1; by2; by3; by6; by7; by8];
lb=[lbx(:);lbm(:);lbz(:);lby(:)];
ub=[ubx(:);ubm(:);ubz(:);uby(:)];
%intcon=1:nd;
%[x,fval,exitflag,output]=intlinprog(f,intcon,A,b,Aeq,beq,lb,ub)
;

%% Gurobi
Agur=[A;Aeq];
bgur=[b;beq];
sensegur=[repmat('<',[size(b),1]); repmat('=',[size(beq),1])];
% Get initial solution
% base_result=load('results_base.mat');
% startx=base_result.results.x;
try
    clear model;
    model.A=sparse(Agur);
    model.obj=f;
    model.rhs=bgur;
    model.lb=lb;
    model.un=ub;
    model.sense=sensegur;
    model.vtype='I';
    model.modelsense='min';
    %model.start=startx;

    gurobi_write(model,'test1.lp');

    clear params;
    params.timelimit=300;
    params.outputflag=0;

    results=gurobi(model,params);

    disp(results)

catch gurobiError
    fprintf('Error reported\n');
end

%% Analyze results
if and(results.runtime<300,results.objbound<Inf)
```

```
    xout=zeros(nn,nj);
    count=1;
    for j=1:nj
        for n=1:nn
            xout(n,j)=round(results.x(count));
            count=count+1;
        end
    end

    cost_out=results.x(1:nx)'*cost(:);
    mout=round(results.x(nx+1:nx+nm)); % time of berthing

    lout=zeros(nn,1); % berthing location
    for n=1:nn
        lout(n)=find(xout(n,:));
    end

    delay_out=mout-a';

    berth_plan={};

else
    disp('Error/no solution/infeasible')
    mout=zeros(nn,1)-1;
    lout=zeros(nn,1)-1;
    cost_out=0;
    delay_out=zeros(nn,1)-1;
    berth_plan={};
    Crane_need={};
    results={};
end
```

Set up and run instances of random inputs

```
% Run niterations experiments with different volume and handling
time
%load('arrival_distribution.mat');
niterations=500;
nn=31; %nr vessels
Vessel_Names={'ACL' 'AL1' 'AL3' 'AL6' 'ATL1-L'  'ATL2' 'ATL-D'
'Loop1' ...
    'Loop2' 'Loop3' 'Loop5' 'EC1' 'EC3' 'EC4' 'EC5' ...
    'EIS/Indamex' 'MD/ECSA' 'MECL' 'MEDUSEC' 'SAE' ...
```

```
    'SAF' 'Tango' 'TAT1' 'TAT2' 'Turkon' 'USEC1/TP11' 'USEC2/TP12'
...
    'USEC5/TP16' 'Z7S' 'ZCA' 'ZCP'};

%Can make one berth at VIG expensive to simulate it's closed
lcost = [104.91 104.91 104.91 104.91 74.68 74.68 131.24 131.24
131.24; ...
    164.41 164.41 164.41 164.41 92.71 92.71 157.57 157.57 157.57;
...
    176.83 176.83 176.83 176.83 109.21 109.21 299.95 299.95
299.95]; %cost per container at each location
% Nr of containers per vessel
ncont = [163 110 0; 496 0 291; 229 0 134; 800 0 125; 667 306 27;
...
    152 40 0; 387 0 13; 995 70 158; 985 0 400; 1180 214 262; ...
    2197 650 1350; 868 0 509; 2170 0 1274; 930 0 546; 620 0 364;
...
    391 64 400; 564 260 76; 418 180 17; 527 118 6; ...
    195 15 0; 106 95 3; 365 0 324; 588 14 282; 999 22 479; ...
    183 0 3; 400 600 50; 1488 284 187; 700 300 0; 502 0 132; ...
    205 0 208; 161 0 30]';
ncont_all = sum(ncont,1);
% Coefficient of variation of container volume
cv_ncont  =  [0.714285714  0.416666667  0.285714286  0.476190476
0.833333333 ...
0.625 0.546448087 0.714285714 0.158730159 0.178571429 0.714285714
...
0.3125  0.25  0.017857143  0.212765957  0.119047619  0.303030303
0.714285714 ...
0.714285714 0.2 0.526315789 0.238095238 0.555555556 0.068493151
...
0.322580645 0.434782609 0.416666667 0.41 0.390221096 0.108831946
0.381992305 ...];
% Standard deviation of container volume
std_ncont = cv_ncont.*ncont_all;
%% Probability distributions
npd1                                                            =
makedist('Normal','mu',sum(ncont(:,1)),'sigma',std_ncont(1));
npd2                                                            =
makedist('Normal','mu',sum(ncont(:,2)),'sigma',std_ncont(2));
npd3                                                            =
makedist('Normal','mu',sum(ncont(:,3)),'sigma',std_ncont(3));
npd4                                                            =
makedist('Normal','mu',sum(ncont(:,4)),'sigma',std_ncont(4));
npd5                                                            =
makedist('Normal','mu',sum(ncont(:,5)),'sigma',std_ncont(5));
```

```
npd6                                                              =
makedist('Normal','mu',sum(ncont(:,6)),'sigma',std_ncont(6));
npd7                                                              =
makedist('Normal','mu',sum(ncont(:,7)),'sigma',std_ncont(7));
npd8                                                              =
makedist('Normal','mu',sum(ncont(:,8)),'sigma',std_ncont(8));
npd9                                                              =
makedist('Normal','mu',sum(ncont(:,9)),'sigma',std_ncont(9));
npd10                                                             =
makedist('Normal','mu',sum(ncont(:,10)),'sigma',std_ncont(10));
npd11                                                             =
makedist('Normal','mu',sum(ncont(:,11)),'sigma',std_ncont(11));
npd12                                                             =
makedist('Normal','mu',sum(ncont(:,12)),'sigma',std_ncont(12));
npd13                                                             =
makedist('Normal','mu',sum(ncont(:,13)),'sigma',std_ncont(13));
npd14                                                             =
makedist('Normal','mu',sum(ncont(:,14)),'sigma',std_ncont(14));
npd15                                                             =
makedist('Normal','mu',sum(ncont(:,15)),'sigma',std_ncont(15));
npd16                                                             =
makedist('Normal','mu',sum(ncont(:,16)),'sigma',std_ncont(16));
npd17                                                             =
makedist('Normal','mu',sum(ncont(:,17)),'sigma',std_ncont(17));
npd18                                                             =
makedist('Normal','mu',sum(ncont(:,18)),'sigma',std_ncont(18));
npd19                                                             =
makedist('Normal','mu',sum(ncont(:,19)),'sigma',std_ncont(19));
npd20                                                             =
makedist('Normal','mu',sum(ncont(:,20)),'sigma',std_ncont(20));
npd21                                                             =
makedist('Normal','mu',sum(ncont(:,21)),'sigma',std_ncont(21));
npd22                                                             =
makedist('Normal','mu',sum(ncont(:,22)),'sigma',std_ncont(22));
npd23                                                             =
makedist('Normal','mu',sum(ncont(:,23)),'sigma',std_ncont(23));
npd24                                                             =
makedist('Normal','mu',sum(ncont(:,24)),'sigma',std_ncont(24));
npd25                                                             =
makedist('Normal','mu',sum(ncont(:,25)),'sigma',std_ncont(25));
npd26                                                             =
makedist('Normal','mu',sum(ncont(:,26)),'sigma',std_ncont(26));
npd27                                                             =
makedist('Normal','mu',sum(ncont(:,27)),'sigma',std_ncont(27));
npd28                                                             =
makedist('Normal','mu',sum(ncont(:,28)),'sigma',std_ncont(28));
```

```
npd29                                                                  =
makedist('Normal','mu',sum(ncont(:,29)),'sigma',std_ncont(29));
npd30                                                                  =
makedist('Normal','mu',sum(ncont(:,30)),'sigma',std_ncont(30));
npd31                                                                  =
makedist('Normal','mu',sum(ncont(:,31)),'sigma',std_ncont(31));

scale_pd=0.30;

npd1                     =                     truncate(npd1,(1-
scale_pd)*sum(ncont(:,1)),(1+scale_pd)*sum(ncont(:,1)));
npd2                     =                     truncate(npd2,(1-
scale_pd)*sum(ncont(:,2)),(1+scale_pd)*sum(ncont(:,2)));
npd3                     =                     truncate(npd3,(1-
scale_pd)*sum(ncont(:,3)),(1+scale_pd)*sum(ncont(:,3)));
npd4                     =                     truncate(npd4,(1-
scale_pd)*sum(ncont(:,4)),(1+scale_pd)*sum(ncont(:,4)));
npd5                     =                     truncate(npd5,(1-
scale_pd)*sum(ncont(:,5)),(1+scale_pd)*sum(ncont(:,5)));
npd6                     =                     truncate(npd6,(1-
scale_pd)*sum(ncont(:,6)),(1+scale_pd)*sum(ncont(:,6)));
npd7                     =                     truncate(npd7,(1-
scale_pd)*sum(ncont(:,7)),(1+scale_pd)*sum(ncont(:,7)));
npd8                     =                     truncate(npd8,(1-
scale_pd)*sum(ncont(:,8)),(1+scale_pd)*sum(ncont(:,8)));
npd9                     =                     truncate(npd9,(1-
scale_pd)*sum(ncont(:,9)),(1+scale_pd)*sum(ncont(:,9)));
npd10                    =                    truncate(npd10,(1-
scale_pd)*sum(ncont(:,10)),(1+scale_pd)*sum(ncont(:,10)));
npd11                    =                    truncate(npd11,(1-
scale_pd)*sum(ncont(:,11)),(1+scale_pd)*sum(ncont(:,11)));
npd12                    =                    truncate(npd12,(1-
scale_pd)*sum(ncont(:,12)),(1+scale_pd)*sum(ncont(:,12)));
npd13                    =                    truncate(npd13,(1-
scale_pd)*sum(ncont(:,13)),(1+scale_pd)*sum(ncont(:,13)));
npd14                    =                    truncate(npd14,(1-
scale_pd)*sum(ncont(:,14)),(1+scale_pd)*sum(ncont(:,14)));
npd15                    =                    truncate(npd15,(1-
scale_pd)*sum(ncont(:,15)),(1+scale_pd)*sum(ncont(:,15)));
npd16                    =                    truncate(npd16,(1-
scale_pd)*sum(ncont(:,16)),(1+scale_pd)*sum(ncont(:,16)));
npd17                    =                    truncate(npd17,(1-
scale_pd)*sum(ncont(:,17)),(1+scale_pd)*sum(ncont(:,17)));
npd18                    =                    truncate(npd18,(1-
scale_pd)*sum(ncont(:,18)),(1+scale_pd)*sum(ncont(:,18)));
npd19                    =                    truncate(npd19,(1-
scale_pd)*sum(ncont(:,19)),(1+scale_pd)*sum(ncont(:,19)));
```

```
npd20                    =                    truncate(npd20,(1-
scale_pd)*sum(ncont(:,20)),(1+scale_pd)*sum(ncont(:,20)));
npd21                    =                    truncate(npd21,(1-
scale_pd)*sum(ncont(:,21)),(1+scale_pd)*sum(ncont(:,21)));
npd22                    =                    truncate(npd22,(1-
scale_pd)*sum(ncont(:,22)),(1+scale_pd)*sum(ncont(:,22)));
npd23                    =                    truncate(npd23,(1-
scale_pd)*sum(ncont(:,23)),(1+scale_pd)*sum(ncont(:,23)));
npd24                    =                    truncate(npd24,(1-
scale_pd)*sum(ncont(:,24)),(1+scale_pd)*sum(ncont(:,24)));
npd25                    =                    truncate(npd25,(1-
scale_pd)*sum(ncont(:,25)),(1+scale_pd)*sum(ncont(:,25)));
npd26                    =                    truncate(npd26,(1-
scale_pd)*sum(ncont(:,26)),(1+scale_pd)*sum(ncont(:,26)));
npd27                    =                    truncate(npd27,(1-
scale_pd)*sum(ncont(:,27)),(1+scale_pd)*sum(ncont(:,27)));
npd28                    =                    truncate(npd28,(1-
scale_pd)*sum(ncont(:,28)),(1+scale_pd)*sum(ncont(:,28)));
npd29                    =                    truncate(npd29,(1-
scale_pd)*sum(ncont(:,29)),(1+scale_pd)*sum(ncont(:,29)));
npd30                    =                    truncate(npd30,(1-
scale_pd)*sum(ncont(:,30)),(1+scale_pd)*sum(ncont(:,30)));
npd31                    =                    truncate(npd31,(1-
scale_pd)*sum(ncont(:,31)),(1+scale_pd)*sum(ncont(:,31)));

late_early_hours=load('late.mat')
[f_lateearly,x_lateearly]=ecdf(late_early_hours);
%plot(x_lateearly,f_lateearly)
x_lateearly(1)=x_lateearly(1)-0.0001;
late_dist                                                     =
makedist('PiecewiseLinear','x',x_lateearly','Fx',f_lateearly');



%%
results_all={};
mout_all=zeros(nn,niterations);
lout_all=zeros(nn,niterations);
cost_out=zeros(niterations,1);
delay_out=zeros(nn,niterations);
berth_plan_all={};
Crane_need_all={};
h_all=zeros(niterations,nn);
n_all=zeros(niterations,nn);
for i=1:niterations
    a = [33 4 12 16 33 34 39 21 3 28 9 42 36 30 9 30 30 22 23 39
39 ...
```

```
    42 21 23 26 27 15 35 31 3 40];
    late = round(random(late_dist,length(a),1)/4);
    a = a+late';
    a(a<1)=1;

    rnd_cont    =    [random(npd1)    random(npd2)    random(npd3)
random(npd4) random(npd5) ...
        random(npd6)   random(npd7)   random(npd8)   random(npd9)
random(npd10) random(npd11) ...
        random(npd12)  random(npd13)  random(npd14)  random(npd15)
random(npd16) random(npd17) ...
        random(npd18)  random(npd19)  random(npd20)  random(npd21)
random(npd22) random(npd23) ...
        random(npd24)  random(npd25)  random(npd26)  random(npd27)
random(npd28) random(npd29) ...
        random(npd30) random(npd31)];
    rnd_cont_norm = rnd_cont./ncont_all;
    ncont_rnd=zeros(3,nn);
    for k=1:nn
        ncont_rnd(:,k) = round(ncont(:,k).*rnd_cont_norm(k));
    end
    ncont_all_modes=sum(ncont_rnd);
    h                                                              =
ceil((0.0099.*ncont_all_modes+5.3442+normrnd(0,3.21,1,nn))/4);
%estimated handling times
    h = max(h,1);
    h_all(i,:)=h;
    n_all(i,:)=ncont_all_modes;

[resultsi,cost_outi,mouti,louti,delay_outi,berth_plani]=solve_pr
oforma(a,h,ncont_rnd,ncont_all_modes,lcost);
    results_all{i}=resultsi;
    mout_all(:,i)=mouti;
    lout_all(:,i)=louti;
    cost_out(i)=cost_outi;
    delay_out(:,i)=delay_outi;
    berth_plan_all{i}=berth_plani;
    i
end

sol_ind=find(sum(mout_all)>0);
sol_nr=length(sol_ind)

% Terminal assignments
l_terminal=zeros(sol_nr,nn);
for i=1:sol_nr
    j=sol_ind(i);
```

```
    l2=lout_all(1:nn,j);
    terminal2=zeros(nn,1); %NIT=1, VIG=2, PMT=3
    for n=1:nn
        if l2(n)<=4
            terminal2(n)=1;
        elseif l2(n)<=6
            terminal2(n)=2;
        else
            terminal2(n)=3;
        end
    end
    l_terminal(i,:)=terminal2;
end

% Location distributions
l_distributions=zeros(nn,3);
for i=1:nn
    l_distributions(i,1)=sum(l_terminal(:,i)==1)/sol_nr;
    l_distributions(i,2)=sum(l_terminal(:,i)==2)/sol_nr;
    l_distributions(i,3)=sum(l_terminal(:,i)==3)/sol_nr;
end

% Berth utilization
atNIT=logical(~(l_terminal-1));
atVIG=logical(~mod(l_terminal,2));
atPMT=logical(~mod(l_terminal,3));
hNIT=sum(atNIT.*h_all(sol_ind,1:nn),2);
hVIG=sum(atVIG.*h_all(sol_ind,1:nn),2);
hPMT=sum(atPMT.*h_all(sol_ind,1:nn),2);
uNIT=hNIT/(4*42);
uVIG=hVIG/(2*42);
uPMT=hPMT/(3*42);

% Volume at each terminal
volNIT=sum(atNIT.*n_all(sol_ind,1:nn),2);
volVIG=sum(atVIG.*n_all(sol_ind,1:nn),2);
volPMT=sum(atPMT.*n_all(sol_ind,1:nn),2);

% Cost
cost_all=zeros(sol_nr,1);
cost_diff=zeros(sol_nr,1);
ncont_out=zeros(sol_nr,1);
nout_temp=sum(n_all,2);
for j=1:sol_nr
    i=sol_ind(j);
    cost2=cost_out(i);
    cost_all(j)=cost2;
```

```
    n_temp=nout_temp(i);
    ncont_out(j)=n_temp;
end
cost_all_norm=cost_all./ncont_out;

% Delays
delay_all=zeros(nn,sol_nr);
for i=1:sol_nr
    j=sol_ind(i);
    delay_all(:,i)=delay_out(:,j);
end
delay_sum=sum(delay_all);
delay_sum=4*delay_sum(delay_sum>=0);
delay_mean_per_service=mean(delay_all,2);
```

Generate schedules for evaluation

```
%% Create l matrix
% NIT=1, VIG=2, PMT=3

l_base = [3 2 0 1 0 0 1 1 0 1 2 0 2 0 2 2 0 0 0 0 0 2 0 0 1 2 1 3
1 2 1];
zero_ind=find(l_base==0);
nit_ind=[3 5 6 9 12 14 17 19 20 23 24];
vig_ind=[3 5 9 12 14 17 18 21 23 24];
pmt_ind=[5 6 18 19 20 21];

l_matrix=[];
%count=1;
l_temp=0;

for i3=1:2
    l_base(3)=i3;
        for i5=1:3
        l_base(5)=i5;
        for i6=1:2
            l_temp=i6;
            if l_temp==1
                l_base(6)=1;
            else
                l_base(6)=3;
            end
            for i9=1:2
                l_base(9)=i9;
                for i12=1:2
                    l_base(12)=i12;
                    for i14=1:2
                        l_base(14)=i14;
                        for i17=1:2
                            l_base(17)=i17;
                            for i18=2:3
                                l_base(18)=i18;
                                for i19=1:2
                                    l_temp=i19;
                                    if l_temp==1
                                        l_base(19)=1;
                                    else
                                        l_base(19)=3;
                                    end
                                    for i20=1:2
                                        l_temp=i20;
                                        if l_temp==1
```

```
                                            l_base(20)=1;
                                        else
                                            l_base(20)=3;
                                        end
                                        for i21=2:3
                                            l_base(21)=i21;
                                            for i23=1:2
                                                l_base(23)=i23;
                                                for i24=1:2

l_base(24)=i24;
                                                    %check     if
within number
                                                    %of   vessels
at each
                                                    %terminal
                                                    if
length(find(l_base==1))<17   &&   length(find(l_base==2))<17   &&
length(find(l_base==3))<6

l_matrix=[l_matrix; l_base];
                                                    end
                                                end
                                            end
                                        end
                                    end
                                end
                            end
                        end
                    end
                end
            end
        end
    end
end
```

Setup evaluation of schedules

```
%% Setup
niterations=1000;
nn=31; %number of vessels

%% Load l_matrix
l_data=load('l_matrix_paper.mat');
```

```
l_matrix=l_data.l_matrix;

%% Setup loop
cost_all=zeros(length(l_matrix),niterations);
delay_all=zeros(length(l_matrix),niterations);
vessel_delays_all=zeros(niterations,nn,length(l_matrix));
NIT_delay_all=zeros(length(l_matrix),niterations);
VIG_delay_all=zeros(length(l_matrix),niterations);
PMT_delay_all=zeros(length(l_matrix),niterations);

for i=1:length(l_matrix)
    l=l_matrix(i,:);

[cost_out,delay_out,vessel_delays_out,NIT_delay_out,VIG_delay_ou
t,PMT_delay_out]=evaluate_l_matrix_paper(l,niterations);
    cost_all(i,:)=cost_out';
    delay_all(i,:)=delay_out';
    vessel_delays_all(:,:,i)=vessel_delays_out;
    NIT_delay_all(i,:)=NIT_delay_out';
    VIG_delay_all(i,:)=VIG_delay_out';
    PMT_delay_all(i,:)=PMT_delay_out';
    i
end
```

Functions for schedule evaluation

```
function
[cost_out,delay_out,vessel_delays_out,NIT_delay_all,VIG_delay_al
l,PMT_delay_all]=evaluate_l_matrix_paper(l,niterations)

nn=31;
nn_boundary=31;
Vessel_Names={'ACL' 'AL1' 'AL3' 'AL6' 'ATL1-L'  'ATL2' 'ATL-D'
'Loop1' ...
    'Loop2' 'Loop3' 'Loop5' 'EC1' 'EC3' 'EC4' 'EC5' ...
    'EIS/Indamex' 'MD/ECSA' 'MECL' 'MEDUSEC' 'SAE' ...
    'SAF' 'Tango' 'TAT1' 'TAT2' 'Turkon' 'USEC1/TP11' 'USEC2/TP12'
...
    'USEC5/TP16' 'Z7S' 'ZCA' 'ZCP'};
% These are the different terminal assignment schedules
% NIT=1, VIG=5, PMT=7
a = [33 4 12 16 33 34 39 42 36 30 9 30 21 3 28 9 30 22 23 39 39
...
    42 21 23 26 27 15 35 31 3 40];
lcost=[104.91 74.68 131.24; 164.41 92.71 157.57; ...
    176.86 109.21 299.95]';
```

```
ncont = [163 110 0; 496 0 291; 229 0 134; 800 0 125; 667 306 27;
...
    152 40 0; 387 0 13; 995 70 158; 985 0 400; 1180 214 262; ...
    2197 650 1350; 868 0 509; 2170 0 1274; 930 0 546; 620 0 364;
...
    391 64 400; 564 260 76; 418 180 17; 527 118 6; ...
    195 15 0; 106 95 3; 365 0 324; 588 14 282; 999 22 479; ...
    183 0 3; 400 600 50; 1488 284 187; 700 300 0; 502 0 132; ...
    205 0 208; 161 0 30]'; %% Check multiplication factor

%% Probability distributions
gmph_dist=makedist('Triangular','a',16,'b',28,'c',39);

ncont_all = sum(ncont,1);
distributions=load('dist.mat');

%%
cost_out=zeros(niterations,1);
delay_out=zeros(niterations,1);
h_out=zeros(niterations,1);
n_all=zeros(niterations,nn);
NIT_plan_all=cell(niterations,1);
VIG_plan_all=cell(niterations,1);
PMT_plan_all=cell(niterations,1);
NIT_delay_all=zeros(niterations,1);
VIG_delay_all=zeros(niterations,1);
PMT_delay_all=zeros(niterations,1);
NIT_time_out=zeros(niterations,1);
VIG_time_out=zeros(niterations,1);
PMT_time_out=zeros(niterations,1);
vessel_delays_out=zeros(niterations,nn);

for i=1:niterations
    late = round(random(late_dist,length(a),1)/4);
    a_rnd = a+late';
    a_rnd(a_rnd<1)=1;

    rnd_cont    =    [random(npd1)    random(npd2)    random(npd3)
random(npd4) random(npd5) ...
        random(npd6)    random(npd7)    random(npd8)    random(npd9)
random(npd10) random(npd11) ...
        random(npd12)  random(npd13)  random(npd14)  random(npd15)
random(npd16) random(npd17) ...
        random(npd18)  random(npd19)  random(npd20)  random(npd21)
random(npd22) random(npd23) ...
        random(npd24)  random(npd25)  random(npd26)  random(npd27)
random(npd28) random(npd29) ...
```

```
        random(npd30) random(npd31)];
    rnd_cont_norm = rnd_cont./ncont_all;
    ncont_rnd=zeros(3,nn);
    for k=1:nn
        ncont_rnd(:,k) = round(ncont(:,k).*rnd_cont_norm(k));
    end
    ncont_all_modes=sum(ncont_rnd);
    n_all(i,:)=ncont_all_modes;

[costi,h_alli,delayi,vessel_delaysi,NITi,VIGi,PMTi,NIT_delayi,VI
G_delayi,PMT_delayi,NIT_timei,VIG_timei,PMT_timei]=evaluate_bert
h_paper(a_rnd,ncont_rnd,l,lcost,gmph_dist);
%     mout_all(:,i)=mouti;
    cost_out(i)=costi;
    delay_out(i)=delayi;
    h_out(i)=h_alli;
    vessel_delays_out(i,:)=vessel_delaysi;
    NIT_plan_all{i,1}=NITi;
    VIG_plan_all{i,1}=VIGi;
    PMT_plan_all{i,1}=PMTi;
    NIT_delay_all(i)=NIT_delayi;
    VIG_delay_all(i)=VIG_delayi;
    PMT_delay_all(i)=PMT_delayi;
    NIT_time_out(i)=NIT_timei;
    VIG_time_out(i)=VIG_timei;
    PMT_time_out(i)=PMT_timei;
    i;
end



function
[cost,h_all,delay,vessel_delays,NIT_plan,VIG_plan,PMT_plan,NIT_d
elay,VIG_delay,PMT_delay,NIT_time,VIG_time,PMT_time]=evaluate_be
rth_paper(a,ncont,l,lcost,gmph_dist)
vessel_ind=1:31;
nn=length(vessel_ind);
cost=0;
vessel_delays=zeros(1,nn);

%% NIT: Berths 1-4
NIT_ind= l==1;
NIT_a=a(NIT_ind);
NIT_ncont=ncont(:,NIT_ind);
NIT_vessels=vessel_ind(NIT_ind);
nn=length(NIT_a);
NIT_plan=zeros(4,100); %changed from 4 to 3
```

```
% State variables
NIT_h=zeros(nn,1);
NIT_delay=0;
NIT_cost=0;
NIT_time=zeros(4,1); %changed from 4 to 3
NIT_avail=zeros(nn,1);

for i=1:nn
    [a_val,a_ind]=min(NIT_a);
    vessel=NIT_vessels(a_ind);
    cprod=random(gmph_dist);
    ncont_all=sum(NIT_ncont(:,a_ind));
    if ncont_all<500
        h=ceil((ncont_all/cprod)/4);
    elseif and(ncont_all>=500,ncont_all<1000)
        h=ceil((ncont_all/(2*cprod))/4);
    elseif and(ncont_all>=1000,ncont_all<2000)
        h=ceil((ncont_all/(3*cprod))/4);
    elseif ncont_all>=2000
        h=ceil((ncont_all/(4*cprod))/4);
    end
    NIT_h(vessel)=h;
    n_cost=lcost(1,:)*NIT_ncont(:,a_ind); % index 1 in lcost for
NIT
    NIT_cost=NIT_cost+n_cost;
    avail=find(NIT_time<a_val);
    NIT_avail(vessel)=sum(avail>0);
    if isempty(avail)==1
        [queue_val,queue_ind]=min(NIT_time);
        NIT_time(queue_ind)=queue_val+h+1;
        NIT_delay=NIT_delay+queue_val-a_val;
        NIT_plan(queue_ind,queue_val:NIT_time)=vessel+100;
        vessel_delays(vessel)=queue_val-a_val;
    elseif length(avail)==1
        berth=avail;
        NIT_time(berth)=a_val+h+1; %adding 4 hour buffer time
        NIT_plan(berth,a_val:a_val+h)=vessel;
    else
        berth=randsample([avail],1);
        NIT_time(berth)=a_val+h+1; %adding 4 hour buffer time
        NIT_plan(berth,a_val:a_val+h)=vessel;
        end
    NIT_a(a_ind)=[];
    NIT_ncont(:,a_ind)=[];
    NIT_vessels(a_ind)=[];
end
```

```
%% VIG: Berths 5-6
VIG_ind= l==2;
VIG_a=a(VIG_ind);
VIG_ncont=ncont(:,VIG_ind);
VIG_vessels=vessel_ind(VIG_ind);
nn=length(VIG_a);
VIG_plan=zeros(2,100);

% State variables
VIG_h=zeros(nn,1);
VIG_delay=0;
VIG_cost=0;
VIG_time=zeros(2,1);
VIG_avail=zeros(nn,1);

for i=1:nn
    [a_val,a_ind]=min(VIG_a);
    vessel=VIG_vessels(a_ind);
    cprod=random(gmph_dist);
    ncont_all=sum(VIG_ncont(:,a_ind));
    if ncont_all<500
        h=ceil((ncont_all/(randsample([1 2],1)*cprod))/4);
    elseif and(ncont_all>=500,ncont_all<1000)
        h=ceil((ncont_all/(randsample([2 3],1)*cprod))/4);
    elseif and(ncont_all>=1000,ncont_all<2000)
        h=ceil((ncont_all/(randsample([3 4],1)*cprod))/4);
    elseif ncont_all>=2000
        h=ceil((ncont_all/(randsample([4 5],1)*cprod))/4);
    end
    VIG_h(vessel)=h;
    n_cost=lcost(2,:)*VIG_ncont(:,a_ind); % index 2 in lcost for
VIG
    VIG_cost=VIG_cost+n_cost;
    avail=find(VIG_time<a_val);
    VIG_avail(vessel)=sum(avail>0);
    if isempty(avail)==1
        [queue_val,queue_ind]=min(VIG_time);
        VIG_time(queue_ind)=queue_val+h+1;
        VIG_delay=VIG_delay+queue_val-a_val;
        VIG_plan(queue_ind,queue_val:VIG_time)=vessel+100;
        vessel_delays(vessel)=queue_val-a_val;
    elseif length(avail)==1
        berth=avail;
        VIG_time(berth)=a_val+h+1; %adding 4 hour buffer time
        VIG_plan(berth,a_val:a_val+h)=vessel;
    else
        berth=randsample([avail],1);
```

```
        VIG_time(berth)=a_val+h+1; %adding 4 hour buffer time
        VIG_plan(berth,a_val:a_val+h)=vessel;
        end
    VIG_a(a_ind)=[];
    VIG_ncont(:,a_ind)=[];
    VIG_vessels(a_ind)=[];
end

%% PMT: Berths 7-9
PMT_ind= l==3;
PMT_a=a(PMT_ind);
PMT_ncont=ncont(:,PMT_ind);
PMT_vessels=vessel_ind(PMT_ind);
nn=length(PMT_a);
PMT_plan=zeros(3,100);

% State variables
PMT_h=zeros(nn,1);
PMT_delay=0;
PMT_cost=0;
PMT_time=zeros(3,1);
PMT_avail=zeros(nn,1);

for i=1:nn
    [a_val,a_ind]=min(PMT_a);
    vessel=PMT_vessels(a_ind);
    cprod=random(gmph_dist);
    ncont_all=sum(PMT_ncont(:,a_ind));
    if ncont_all<500
        h=ceil((ncont_all/cprod)/4);
    elseif and(ncont_all>=500,ncont_all<1000)
        h=ceil((ncont_all/(2*cprod))/4);
    elseif and(ncont_all>=1000,ncont_all<2000)
        h=ceil((ncont_all/(3*cprod))/4);
    elseif ncont_all>=2000
        h=ceil((ncont_all/(4*cprod))/4);
    end
    PMT_h(vessel)=h;
    n_cost=lcost(3,:)*PMT_ncont(:,a_ind); % index 3 in lcost for
PMT
    PMT_cost=PMT_cost+n_cost;
    avail=find(PMT_time<a_val);
    PMT_avail(vessel)=sum(avail>0);
    if isempty(avail)==1
        [queue_val,queue_ind]=min(PMT_time);
        PMT_time(queue_ind)=queue_val+h+1;
        PMT_delay=PMT_delay+queue_val-a_val;
```

```
        PMT_plan(queue_ind,queue_val:PMT_time)=vessel+100;
        vessel_delays(vessel)=queue_val-a_val;
    elseif length(avail)==1
        berth=avail;
        PMT_time(berth)=a_val+h+1; %adding 4 hour buffer time
        PMT_plan(berth,a_val:a_val+h)=vessel;
    else
        berth=randsample([avail],1);
        PMT_time(berth)=a_val+h+1; %adding 4 hour buffer time
        PMT_plan(berth,a_val:a_val+h)=vessel;
    end
    PMT_a(a_ind)=[];
    PMT_ncont(:,a_ind)=[];
    PMT_vessels(a_ind)=[];
end

cost=NIT_cost+VIG_cost+PMT_cost;
h_all=sum(NIT_h)+sum(VIG_h)+sum(PMT_h);
delay=NIT_delay+VIG_delay+PMT_delay;
NIT_time=max(NIT_time)-1;
VIG_time=max(VIG_time)-1;
PMT_time=max(PMT_time)-1;
```