

WATERWAY SYSTEM MAINTENANCE OPTIMIZATION

A Dissertation

by

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## ABSTRACT

Coastal lines, harbors/ports, and inland waterways constitute the marine transportation system, a major component of the United States freight system, carrying a vast majority of foreign imports and exports and a significant amount of domestic freight. This system needs regular maintenance. US Army Corps of Engineers (USACE) is in charge of the waterway system maintenance. However, the limited maintenance budget needs to accommodate a large number of maintenance requests for dredging and dam repair, etc. The requests often exceed the budget available by much. A decision facing the USACE management is what projects to fund and how to select them. This research aims at providing the necessary models and tools to facilitate maintenance decisions at the USACE. The objective is to maximize the overall system improvement under annual limited budget. The underlying problem can be modeled as a knapsack problem with an additional constraint that increases the problem complexity. The additional constraints describe the benefit interdependency of different maintenance projects due to the waterways network effect.

This research tackles the maintenance problem at different levels. First, an integer selection model is developed to find the optimal set of dredging projects (waterway sediment removal operation) and some heuristics are developed to provide near-optimal solutions in computationally guaranteed polynomial time. Next, a model is developed to allow partial dredging. Partial dredging means partially conducting the requested dredging operation. The model is able to determine the percentage of the dredging depth to fund instead of a zero-one dredging decision for each project.

Further, a stochastic problem is considered regarding to the probabilistic shoaling process. To solve the probabilistic problem, two methods are designed: an analytical model that takes account of probability in terms of expected values, and a stochastic optimization approach was developed based on Monte-Carlo simulation.

Finally, the problem is modeled in a multi-modal context where the maintenance decisions are made simultaneously on dredging and lock/dam improvement. In this multimodal model, the effect of landside modes' capacity is considered comprehensively. All the developed methods are tested with real examples from US marine network and their performance is approved by comparison to real situation.

## DEDICATION

This dissertation is dedicated to my amazing family: my lovely wife Mahsa, my dearest mother Jila, and my wonderful brother Nima. It would not have happened without their encouragement, support and love. Finally, I would like to dedicate this dissertation to the memory of my beloved father Ali, who always inspired and encouraged me to be a better human.

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## NOMENCLATURE

USACE	US Army Corps of Engineers
OD	Origin- Destination
SAA	Sample Average Approximation
O&M	Operation and Maintenance

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## CHAPTER I

### INTRODUCTION

Coastal ports, waterways, and channels constitute a major component of the United States freight transportation system, carrying the majority of foreign imports and exports plus a significant amount of domestic freight. According to the U.S. Department of Transportation's Maritime Administration, the combined foreign trade value took 22 percent of U.S. GDP in 2006; and keeping same growth rate it is expected to meet 35 percent and 60 percent of GDP respectively by 2020 and 2030, respectively. According to this forecast, marine transportation will handle 95percent of U.S. foreign trade, thereby maintaining its role as a vital contributor to U.S. GDP and national wellbeing[1]. The waterway transportation system has gained attention in recent years because of its energy efficiency compared with other modes as well as its role in promoting international commerce. Moreover, as landside modes of transport such as rail and highway become ever more congested, and as fuel prices continue to climb, there is increasing interest in expanding waterborne trade routes for domestic freight shipments.

One big problem that inland channels are dealing with is shoaling (loosing depth) due to settlement of sediments carried by tidal and longshore currents. This natural process decreases the effective depth of channels and the capacity available for moving large vessels. To address this issue, dredging operations are conducted to provide adequate depth for vessel navigation and to keep the channel up to its capacity. However, due to a limited budget, every fiscal year the US Army Corps of Engineers

(ACE), who is in charge of dredging operations, needs to select the optimal (near optimum) dredging decisions (maintenance decisions include defining both dredging locations and dredging extents) among all potential ones to fund in order to maintain an adequate capacity of the waterway system. The waterway system includes the waterway segments, ports, and docks/dams. This research focuses on modeling the dredging decision problem and waterway maintenance in general with an objective of maximizing the waterway or system efficiency. Solving this problem helps to improve the system economy through both optimizing fund allocation, and enhancing the transportation network. This study is the first of its kind to employ an analytical method to model interdependent waterway networks maintenance problem.

The main source of complexity in solving this optimization problem originates from the fact that the benefit from dredging a channel is interdependent with other channels subject to dredging. This property is intuitive indeed, bringing one port to a certain depth does not mean large vessels can operate to another port because the other port may fall short of a certain depth for the large vehicle to operate. In other words, the benefit of carrying through traffic depends on all the dredging projects along the shipping path being funded. In addition, the waterway system belongs to a broader transportation system that encompasses other waterborne facilities as well as landside modes such as highways and railways. Regarding waterborne facilities, ports and locks/dams are critical elements in the waterborne transportation system, which demands periodic maintenance, a billion dollar business every year. All these relationships reveal

the dependency of waterways with all other components of an intermodal transportation system.

The other issue that adds to the complexity of maintenance programming of waterways is the randomness of the shoaling effect. Usually channels experience shoaling some period after that they are dredged, where deeper channels have the higher probability of losing depth. Thus, planning for optimal maintenance scenarios is an inherently probabilistic problem that influences the system reliability. This study at the last step would evaluate the effect of this probabilistic process on the optimal solution and the system reliability.

### **1.1 Problem Statement**

This research aims to develop analytical models for optimizing US waterway maintenance on an intermodal network. This network includes the US marine network comprised of waterway segments, dams/locks, and ports along with the landside transportation network connected to endpoint ports comprising highways and railways. In this problem intermodal network is represented by a set of nodes and a set of links. Each link may be construed as an entity with a through capacity for cargo movements. Commodities go between origins/destinations, typically referred to in literature as OD flows. Each origin or destination is just a point on the network. Each OD flow goes through the network along a specific path that consists of a set of connected links. Each element has a capacity that can be improved, and the magnitude of that improvement is determined by the extent of the maintenance action taken. Likewise, the maintenance

cost for each element is also a function of the extent of the maintenance action. The network maintenance is limited to the maintenance budget each year for all the maintenance requests proposed for the same year. Each maintenance package has a requested budget and an expected improvement to the element in terms of dredging depth (to rivers or ports) or increased operational hours (to locks/dams). Therefore, the objective of solving this problem is to select maintenance projects that maximize the total network flow efficiency or minimize the total traveling cost. This problem is broken into several smaller problems that are subject to solve in different chapters. The following paragraphs portray these sub-problems and proposed models to solve them.

At first attempt as in chapter 3, this research addresses the problem of determining the optimal dredging scenarios, or optimal fund allocation, for the water system components that maximize overall performance of the system, excluding components connected to the waterway system. The crucial constraint that is taken to the model and changes this model to a complex one is considering the inter-dependencies between different segments of the waterway network. To solve this problem, first a mixed integer programming method (MIP) is proposed which is an all-or-nothing decision model to find the optimal dredging locations. Then heuristic methods are proposed to solve the problem that are able to find the near optimal solutions.

In chapter 4 the problem is expanded to allow for partial funding. Partial funding means a dredging project may be partially funded when multiple levels of maintenance are possible. For example, if a maintenance dredging request calls for a 3- foot increase in navigable depth for a shoaled channel, the continuous model allows consideration of

dredging options that increase the channel depth anywhere between 0 and 3 feet, assuming for simplicity that the cost of dredging can be expressed as a continuous function of the increase in channel depth. The developed model allows the search algorithm to explore the continuum of costs and benefits at individual projects and the impact on system-level efficiencies.

Chapter 5 extends the problem in previous chapters under uncertainties due to natural probabilistic shoaling process. Here probabilistic shoaling means that shoaling happens after dredging operation according to a certain probability distribution. Example is that a deeper draft has a faster shoaling process. Deeper draft costs more to maintain. This chapter provides two methods for solving the extended stochastic problem. In fact, the benefits from dredging a particular waterway segment in the models proposed in pervious chapters only depend on the depth to which the segment is dredged. Insofar as the dredging benefits, one needs to consider the possibility of loss of depth due to subsequent shoaling in upcoming time period after dredging. The shoaling depends upon many different factors like geological and hydrologic conditions. However, in general, the deepened channels could trap sediments more easily and are more prone to future shoaling. They lose depth at a faster rate than shallower portions of channel[2].

Subsequently, one needs to account for random effects of shoaling according to reality. In this chapter, two methods are developed for solving the stochastic problem, the first is a proxy deterministic method that uses the expected value of shoaled depth to make decision, and the second is a stochastic method based on Monte Carlo simulation referred as Sample Average Approximation (SAA).

Chapter 6 extends the problem scale into a multi-modal network by considering the locks/dams and landside transportation as new elements of the system and develops the maintenance problem in a multimodal context. A multimodal network positions the waterway system realistically onto a national or regional freight system that better serve stakeholders. However, this annex imposes new restrictions from both locks/dams and landside transportation. These restrictions include availability of locks/dams (working in operation order) along waterways and the restrictions that are imposed by capacity of landside transportation connected to ports. Thus, the model prohibits generating solutions from a limited point of view where the improved waterway capacity gets bigger than the available landside capacity or exceeds the capacity of connecting locks/dams. In addition to the multi-modal consideration of the problem, a new perspective is adopted to define the maintenance problem. In former chapters, the problem is modeled as a maximization problem that aims to maximize the total throughput by providing more draft. However, in reality waterway system maintenance does not add up the demand and the total throughput. Instead it diminishes the transportation cost and increase the fluidity of the system. To bring this consideration into the model, a new model is developed that finds the optimal budget allocation by minimizing the cost of transportation through maintaining waterway system including dredging waterway channels or lock/dam improvement.



## 1.2 Research Objectives

The goal of this study is to provide a mathematical modeling platform for optimally maintaining the waterways (maximizing the efficiency or minimizing the cost). To this end this study attempts to fulfill the following objectives:

- To find a group of projects (dredging) from the set of all potential ones, for presumed depths of dredging that optimize the system performance. The problem statement addressing this objective is an extended version of Nap Sack problem, in which selection of each project affects the other ones' benefit.
- To extend the model of part A by identifying the optimal scenarios that allow for partial funding. Meaning to determine both optimal depths and locations of dredging simultaneously. The model approaching this objective shall enable the framework to put out continuous results representing each segment optimal decided depth for dredging.
- To consider the effects of randomness on the optimal results and develop an approach to find optimal or near optimal solutions for this condition.
- To extend the model to foresee all the multimodal network components that restrict the performance of waterway segments. This objective wants to bring the dependency of waterways to other elements of multimodal network into account in addition to the interconnection between different waterway segments.

### **1.3 Research Organization**

This research develops a set of mathematical models to decide about the optimal set of maintenance actions as well as some heuristic methods to provide time efficient near optimal solutions. The order of this research is organized as follows:

#### *1.3.1 Chapter II: Background*

This chapter represents a review on the literature of several subjects, including waterway maintenance, selecting problem, multimodal freight network design, probabilistic models in maintenance studies, and reliability.

#### *1.3.2 Chapter III: All or Nothing Dredging Model*

This chapter introduces the first version of dredging problem where the goal is to find a set of dredging scenarios that maximizes the network efficiency. In this chapter we take the historical additional tonnage that passed through the route due to higher draft as the index for efficiency. An integer 0-1 selection model is developed to solve this problem optimally. In addition some heuristics are introduced that provide near optimal solutions in shorter time. The results of the model on a real network are presented at the end of chapter.

#### *1.3.3 Chapter IV: Continuous Dredging Model*

This chapter extends the problem in chapter 3 by allowing to take account of partial dredging. The model proposed to solve this problem is called continuous model since it

is able to select the optimal depth of dredging instead of only all-non decision. Like the previous chapter some heuristics are developed for faster running time. At the end the continuous model and heuristics are applied on a real network and results are presented at the end of chapter.

#### *1.3.4 Chapter V: Probabilistic Dredging Model*

Chapter VI represents the stochastic version of the problem. In this chapter the existence of uncertainty due to probabilistic nature of shoaling is involved in the problem and corresponding models. First, an analytical model that takes account of probability in terms of expected values is proposed over the continuous model. Next a stochastic optimization approach is developed based on Monte-Carlo simulation that approximates the solution by averaging over enumerated random samples. The results of both methods application are illustrated and compared.

#### *1.3.5 Chapter VI: Minimization Cost Model on a Probabilistic Multimodal Network*

The dredging problem range in this chapter expands to consider the problem in a multi-modal network. A marine transportation system in addition to its waterway network consists of locks/dams as other important elements of the waterway system that have significant effect on the marine system performance. In addition, from a multi-modal perspective, the waterside network is connected to landside modes (highway and railroad network). In fact, the major portion of the commodity that is transported through the waterway network must take landside modes to reach to its OD. Accordingly, the

problem now could be extended and modeled in the most general context: in the form of a multi-modal network programming. Hence, this chapter provides a model that considers the problem in a multi-modal network and embraces all elements of such network including: waterways, locks/dams in waterside as well as highways and railroads on land-side.

This chapter also introduces a new approach for modeling the maintenance projects' budget allocation. The models that have been developed so far aim to determine the optimal maintenance plan through maximizing the throughput of the whole waterway system. Although this approach could define the prioritization of projects to receive their requested budget, it does not completely comply with the actual state of the marine network. In reality, the throughput is almost fixed and very resistant to change. The major factor that is influenced by the decay of the waterway network is the cost of transportation and the fluidity of network. The model developed in this chapter solves the problem of optimal maintenance by minimizing the inducted cost due to system decay. The results of the model on a real network are demonstrated at the end.

### *1.3.6 Chapter VII: Conclusion*

This chapter sums up all the drawn conclusions from different chapters and proposes the outline for future researches and studies.

## CHAPTER II

### BACKGROUND

This chapter presents study of literature over all the similar studies and researches regarding to waterborne facility maintenance operation. In addition, there would be reviews on other studies regarding to particular methods used in methodology chapters, or maintenance models for different backgrounds and other modes of transportation such as highway segments.

Before starting the review over the literature of methodologies in this study, it is required to provide a brief background about the waterway system. The principal infrastructural components of the marine system are: waterways including navigable waterways and their associated infrastructures like locks/dams, and bridges, ports, intermodal connections, and vessels and vehicles[3]. This research focuses on the programming the maintenance of the waterways, particularly waterways channels and locks/dams. The main improvement and maintenance over the channels is dredging that is the operation of deepening the waterways by removing sediments from their bed. Deeper channels allow larger vessels and more cost-efficient marine transportation. The USACE undertakes the dredging process annually and it is the most costly operation in their civil work budget[4]. Only in 2014, USACE removed 185.9 million cubic yards of materials nationwide for the cost of \$1,527.0 million[5]. The main reason for continuously annual dredging is the phenomena of shoaling that is settling the tidal sediments at rivers bed. The shoaling happens through six mechanisms including:

channel migration, morphodynamic pathways, loss of hydraulic gradient, abandonment, bed form regimes, regional siltation, and geotechnical reasons. Each of these mechanism causes a specific pattern of effective depth reduction[6]. In general, the shoaling due to any of mentioned results is a random process that can negatively affect the effective navigable depth of waterway channels continuously and causes the need for dredging.

The other important components of the waterway system are locks/dams. There are 207 locks/dams chambers on 27 on 27 inland rivers and intracoastal waterways system segments. These locks/dams are the main connections between river segments with different levels. In the waterway system, usually each route consists from a number of waterway segments and locks/dams. Thus, a vessel should travel along the whole system to move the freight from its origin to its destination. The locks/dams' unexpected failure sources significant delay in vessels travel time that causes substantial cost. By aging the system the likelihood and expected delay is increasing over the system. Right now, about 54% of the Inland Marine Transportation System's (IMTS) infrastructures are more than 50 years old and 36% are more than 70 years old [7]. Thus, locks/dams also need funding for being maintained to improve their performance and minimize the risk of failure. In [8], the authors have analyzed and prioritized the locks/dams that need rehabilitation funding on the Upper Mississippi River, the Illinois Waterway, and the Ohio River. The cost of locks/dams' maintenance and rehabilitation ranges from couple of million to hundreds of million dollars depending on age, size, and the condition of locks/dams.

In continuous, partial reviews are presented to address literatures corresponding to different models that are developed in this study including modeling dredging maintenance, selecting problem, multimodal freight network design, and probabilistic models in maintenance studies. These reviews include the most pertinent antecedent studies conducted to model waterway system maintenance programming (particularly the dredging operation). However, due to lack of enough literature in waterborne area, some literatures are provided from other modes facility maintenance studies.

## **2.1 Modeling Dredging Maintenance**

This section provides a review on researches regarding to waterway dredging maintenance.

The first applications of operation research techniques regarding to dredging modeling goes back to studies like managing dredge disposals materials done by Ford [9], [10] that he used linear and integer programming to identify efficient dredge-material disposal strategies in Delaware River. Hochstein [11] as well used specific methodology to determine the navigable channel depths by maximizing the net benefit. They first defined all the environmental constraints and then estimated the cost due to dimension of a single reach of an open river and the size of tows that use that channel. Their model at the last indicates the best channel dimension and the best types of tows to maximize the net benefit.

Lund [12] developed a methodology to schedule optimal dredging equipment and operations in space and time when allowing for advanced dredging. Advanced dredging

is to dredge more than authorized depth in order to reduce the frequency of dredging operation due to sediments. The goal of the study is to minimize the net present value of all present and future dredging costs over the long term and lower the risk of sediment encroachment for a single reach channel. He considered uncertainty in sediment encroachment where sedimentation rate is independently distributed, thus he used the expected cost in scheduling the dredging operation. The developed methods are only applicable for channels with known spatial pattern along the reach. The models are originated from optimal replacement and capacity expansion theories (Jorgenson et al. [13]; Freidenfelds[14]). The results offered advanced dredging and showed that advanced dredging in a certain range is an economical choice for scheduling. However, this research only considers programming for a single reach and does not see the interdependency existing on a network.

Ratick et al. [15] developed a reliability dynamic model to program the dredging operation. They innovated a simulation-optimization approach with combining a dynamic location model, that decides optimal schedule and dredging location, with a hydrological simulation model to consider the uncertainty of channel condition. The developed approach is designed to determine types and sizes of dredges for different reliability levels. The model also can determine the assignment of demobilization and mobilization costs when facilities are moved from one location to another. In addition, it allows advance dredging to address future needs when it eventuates to lower overall cost. The model developed in this study, though, allows for planning of a single channel



consisting of several reaches and does not offer a global decision making among all channels in a network.

Lansey and Menon [16] likewise, considering a single channel developed a least cost model that aims to minimize the total channel expected operations cost on a long run while guarantees the adequate flow depths through scheduling channel inspection and dredging. Subsequently their proposed model is developed to be able of considering the uncertainty of flows as well as the reliability of the channel due to uncertain amount of shoaling. The authors considered two costs, first the cost of equipment and facilities and all other regarding costs, and the second cost regarding to the expected failure cost due to the inadequacy of channel depth for class of bigger vessels which is an expected cost since flow is uncertain.

Ratick and Morehouse Garriga [17] studied programing and scheduling the optimal dredging allocations on a single channel incorporating different environmental and economic uncertainties. The authors proposed a risk-based spatial decision support system to plan the advanced dredging maintenance actions on a water navigation channel. To describe the system, they used a mixed-integer model that takes account of making balance between cost and channel reliability for a given annual budget. Besides the probabilistic sedimentation process, they considered other uncertainties like dredge plant productivity and volatile economic using sensitivity analysis. The model determines the sequences of dredging allocations and actions that provides the highest level of reliability with limited resources-time, funds, and equipment. As a result, they

developed a computer program that assists operations managers about when to call dredges to various reach locations along a channel.

Blazquez et al [18] studied dredging operations, but from the perspective of optimally utilizing dredging equipment in consideration of environmental impact.

Mayer and Waters [19] proposed an optimal maintenance model for a single section. They considered two different dredging decisions: advance dredging (more than authorized channel dimension) and differed dredging (reduced in depth). The authors proposed a model that uses differential equations to seek for a solution that balances between operational efficiencies and safety. Thus, they developed a methodology to plan and schedule an optimal dredging operation. They used sediment inventory model (SIM) extended from classic inventory model for operations. Three cases are evaluated regarding to three different conditions of dredging operation, for each case an optimal depth and dredging cycle times are derived according to presumed conditions. The basic examples from this study suggested that for linear cost structures the optimal solution both economically and navigation-wise achieves from dredging to maximum acceptable depth. In spite of the good parametric perspective that the proposed model provided, the proposed model is only usable for standalone models and not usable in real problems. First, because the methodology is developed for a single decision and not is not network wise driven accordingly, it also cannot see the interdependencies between correlated projects, and second; it does not see the fund limitation concern and competition between projects to receive the funding.

## 2.2 Interdependent Projects Scheduling

Ting and Schonfeld [20] used a new approach named simultaneous perturbation stochastic approximation (SPSA) to minimize the total tow delay. This approach determines how much improvement to provide at particular lock sites and when to implement the improvement. The developed approach allows for optimal selection, sizing, and sequencing of expansion projects on locks.

Jong and Schonfeld [21] studied the problem of selection, sequencing, and scheduling of maintenance projects on interdependent waterway networks while the budget is limited. They aimed to minimize the present value of total cost over the planning horizon through minimizing the total delay on locks. Due to the complexity of the problem and difficulties for developing analytical models, they proposed a simulation-based genetic algorithm approach to solve the problem. Wang and Schonfeld [22] considered the same problem of locks maintenance and rehabilitation. However, they developed the previous approach combining simulation and genetic algorithms to count for scheduling locks on a multiyear planning horizon. The complexity of the problem comes from the interdependency of project delays and construction cost of each project. The authors mention that the computer simulation coupled with genetic algorithms is applicable to real big size network; however, it requires significant time.

Tao and Schonfeld [23, 24] developed some kind of genetic algorithm to schedule roadway improvement projects on an interdependent networks. The improvement projects have intricate correlation because of the network effects on travelers' cost. However, evaluating the overall system cost is an effortful job due to the

uncertainty of travel times and improvement project costs. Thus, the authors developed island models as variants of traditional genetic algorithms to solve the stochastic problem of selecting and scheduling interdependent roadway segments considering the limited resources.

Wang and Schonfeld [25] continued to previous studies [21, 22] developed another simulation based optimization model to select and schedule interdependent waterway projects. They used a genetic algorithm to solve the model. In addition, several other papers recognized the interrelationship constraint in infrastructure maintenance in different contexts such as Folga *et al.* (2009).

The above-mentioned study carried out by Schonfeld and his collaborators is generally based on genetic algorithm and computer simulation. However, this research provides an analytical model that can produce the optimal solution for both dredging and lock maintenance. Besides this study offers some intuitive and easy-to-use heuristic methods are developed to attain some near optimal solutions.

The dredging project selection problem under the budget constraint is a kind of combinatorial optimization problem. From the first studies that considered the interdependency of general projects is Nemhauser and Ullman [26], who proposed a dynamic programming approach to take the interdependency into account. The only interdependency they considered though, is pair-wise relation. On the other hand, the project inter-dependency in this research is more complicated, and is largely attributed to a network effect similar to Tao and Schonfeld [24]. As an instance, restored capacity between an origin destination (OD) pair is dependent on all projects along this route to

be completed, which makes it impossible to use in Nemhauser and Ullman's [26] method. In other important study, Weingartner [27] provided a complete survey of methodologies to the capital allocation problem including integer programming, linear programming and dynamic programming methods.

In a more general perspective in transportation concerning project selection and capital allocation, Melachrinoudis and Kozanidis [28] developed a mixed integer knapsack model and used a branch and bound algorithm to solve the problem of highway improvement fund allocation that does not realize the interdependency between maintenance projects as it is considered in this research.

The interdependency between different components of infrastructure, or in other words, the network effect of components, differs from one circumstance to another. For each specific case we may need a vastly different models and solution algorithms. For instance, the project interdependency in this problem as explained above is different from those discussed in literature. Today, the computational power and availability of computational resources has dramatically improved. Many problems that were not able to be solved to optimum can be solved now with widely available optimization software. In this paper, we develop models and solution algorithms specifically for this waterway dredging project selection problem, which by itself is critically important to maintaining this low cost, vast waterway system.

### 2.3 Multimodal Freight Network Design

Multi modal freight transportation has been extensively studied in transportation literature. This section provides an inquiry on several of the most pertinent studies dealing with waterways as a part of multimodal network. Figure 1 illustrates an abstract of the end to end connection of water, rail and road modes, which will be the topic of this section.

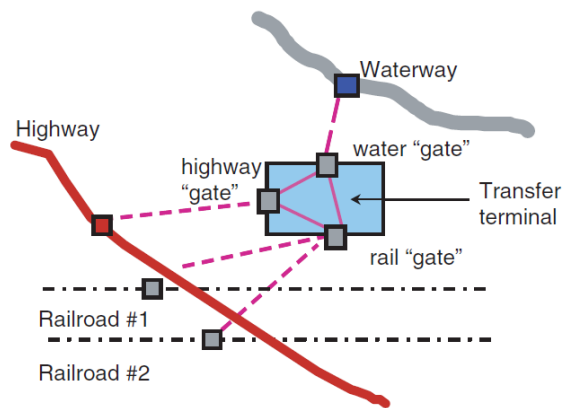


Figure 1 A portrayal of intermodal connection [29]

Harker and Friesz [30] are among the first who considered this multi modal freight transport. They developed an analytical predictive model of freight transportation. They used combination of two spatial price equilibrium and freight network equilibrium models to handle generation, distribution, modal split and assignment of freight movements simultaneously. Harker and Friesz [31] changed the representation of the mathematical model and developed a nonlinear complementarity

formulation in addition to a variation inequality formulation; they then investigated the existence and uniqueness of the solution.

Guelat et al. [32] developed a normative multiproduct multi modal assignment in a strategic level. This model solves a system-optimal assignment problem with the objective of minimizing the total delay and transfers costs. They used a Gauss-Seidel-Linear Approximation Algorithm to solve the proposed model.

Southworth et al. [29] explored an approach to simulate multi modal freight flow, known as regional routing model (RRM). They tried to use the most recent data of commodity production, consumption, flow, and transportation cost to attune the 2002 RRM model. The RRM can serve as an element to base a framework for modeling waterway investment. It is capable of developing sort of origin, destination, commodity and mode traffic flows, besides is capacitated to perform a congestion-sensitive and commodity-specific freight assignment on different sections of multimodal network. They implemented their assignment model on a set of linked national highway, waterway, and railway networks with many of major link connections through truck–rail and truck–waterway terminals. They adopted two options for implementing the assignment: simultaneous and sequential assignment to modes and routes. The result represented kind of Wardrop equilibrium happens and shippers choose the mode/route with the minimized cost. In this model, the restriction on waterway is seen as a delay function, which effects on selection of waterway segments as well as rail and road congestion.

In another study, Mahmassani et al. [33] evaluated the multi-product intermodal freight transportation network by developing a dynamic network simulation based assignment platform. Their framework included three elements: a multimodal freight network simulation part, a multimodal freight assignment part, and a multiple product intermodal shortest path procedure. For the first component, to mimic the transfer delay met by each shipment, they used a bulk queuing. The second component finds the network flow patterns among a mod-path set using multiple product intermodal shortest path component, based upon the link travel cost and transfer delay of each node achieved from the first component. The advantage of this model to others is its capability to determine individual shipment mode–path choice behavior, conveyance link moving, and individual shipment terminal transfer.

Caris et al. [34] surveyed the planning problem in intermodal freight transportation literature. They considered problems like improvement projects over drayage, network, and terminal operators.

Yamada et al. [35] considered a multimodal freight transport network to model an investment plan particularly for development and interregional freight networks and terminals. Their objective is to find a set of optimum actions to develop the existing network. To approach this aim, their model selects a set of optimum actions, such as expanding the in current use road and rail segments, sea links, terminals or founding new infrastructures, from a collection of potential scenarios. The kind of integrated framework that they established allows to make the investment decision in a coordinated way and minimize the cost of system development and facility locating. They propose a



bi-level model where the upper level takes account of searching for the optimal set of actions to maximize the benefit to cost ratio. Meanwhile, the lower level feeds the upper level with the traffic flow on different links of network by employing a multimodal multiclass-user traffic assignment technique. They used a heuristic genetic based method to solve the upper level, which is a combinatorial optimization. Using a multiclass-user model, the model can select either an improvement or adding a new link or any other action[2].

#### **2.4 Probabilistic Models for Maintenance Projects**

Usually maintenance and rehabilitation (M&R) of transportation infrastructures is based upon the inspection of facilities and collecting information of the current condition. The inspected information sometimes is treated as error-free data, whereas there usually are significant errors in data investigation process originating from different sources. Error in surveying the exact profile of settled sediments and consequently the volume of dredging operation is an example of existing errors in optimal maintenance operation. Regardless of the error origin, this bias in facility condition state causes an extent of uncertainty among input data. In waterway networks though, the randomness and uncertainties exist due to the shoaling process happening in the river beds. Shoaling is the process of returning the sediments and deposits to river bed and decreasing the effective depth of river. According to many different geographic and hydrologic factors, the deepened channels usually experience losing the depth due to shoaling shortly after dredging, however the occurrence and the scale of shoaling is a random factor. The

higher dredging depth has higher chance to experience shoaling. In past two decades, many researchers have tried to address the effect of underlined uncertainty in M&R modeling. The existence of such uncertainty can impose additional life-cycle cost to system or result in a solution far from optimum. This section would have a review on similar literature.

Involving the uncertainty in maintenance and rehabilitation (M&R) of infrastructures, first time was introduced by Golabi et al. [36]. The authors developed pavement management system to find the best policies for maintaining the Arizona State highway pavement. The proposed model is an optimization model termed as Network Optimization System (NOS). This model is capable of capturing the dynamic and probabilistic characteristics of pavement maintenance. It eliminates uncertainty resulting from different M&R actions using a Markov Decision Process (MDP). The main elements of MDP are road conditions or states and the maintenance actions where could be undertaken. This methodology enables us to examine current and expected conditions of pavement, assuming a selected action among a set of actions. The real world results of model application disclosed a huge saving of money on life-cycle costs. Some other researchers like Camahan et al. [37], Davis and Carnahan [38], and Carnahan [39] later adopted same MDP methodology for infrastructures, particularly pavement, maintenance. In all these inquiries, both facility conditions and time horizon are modeled by discrete time transitional probabilities.

Madnat [40] and Madanat and Ben-Akiva [41] were the first who considered the error effect in measurement of facility condition on management process. A Latent

Markov Decision Process (LMDP) is employed in these studies to observe the effect of measurement uncertainties. The proposed method is also capable of determining the value of more accurate data.

Mbwana and Turnquist [42] proposed a new formulation using Markov transition probabilities to model the pavement management system at the network level which allows for link-specific policy making through optimization. This characteristic facilitates change from network-level to project-level solution.

Later Smilowitz and Madnat [43] extended the LMDP methodology to include network constraints. The authors approached this development using linear programming with network constraints in conjunction with randomized policies, which determines the optimum probabilities for different maintenance actions instead of specifying a single optimal action. They proposed different versions of formulation for two cases of transient finite-horizon, and a steady state infinite-horizon.

In both above studies, transition probabilities are used to explain decay process and discrete condition rating sets represent the facility condition. At the same time, Kuhn and Madanat [44] proposed a robust optimization to consider Epistemic and parametric uncertainties. In this method of optimization, the data are uncertain and belongs to a set of uncertainty. The objective function will realize the optimal expected cost given an uncertainty range, though, when there is not enough information, regarding to uncertainty set available, the worst case is optimized. This study is an extension of Kuhn and Madanat [45] where the authors for the first time applied the robust optimization for facility management to deal with epistemic uncertainty. Using a parametric

methodology, they verified the capability of this optimization method in reducing the maintenance cost when there is uncertainty in modeling of infrastructures. They also proposed an algorithm to solve the problem.

Seyedshohadaie et al. [46] in a similar study investigated the transportation infrastructure networks M&R and developed a method to determine risk-averse maintenance policies under deterioration uncertainty. They proposed methodology uses a MDP and is capable to guarantee a level of performance under predetermined level of uncertainty. The difference between this study and other similar studies is in use of a quantitative measure of risk to manage the uncertainty in the deterioration process. This measure is fundamental in finding the optimal funding policies for both long-term and short-term programming.

## CHAPTER III

### ALL OR NOTHING DREDGING MODEL\*

This chapter regards the problem of fund allocation to dredging projects that are carried out with U.S. Army Corps of Engineers (USACE) annually. The problem is to decide a set of dredging actions among a big collection of potential projects that compete to receive required funding from a limited budget source.

The challenge for solving this problem originates from the complicated interdependent relationship between different projects. Waterway system like other networks is affected by network wide constraints that connect different segments together and correspond decisions on each segment dependent on others. Likewise, the benefit from dredging project is completely dependent on the other projects and their condition of other elements of network. For example if a project only deepens one channel on a route but leaves the others the whole route cannot benefit from increased depth all along the route and the applied dredging operation is fruitless.

This chapter develops two linear-integer programming models in addition to some heuristic algorithms that allow selecting the optimal and near optimal dredging projects to fund under budget constraint and considering the interdependency. The models then are applied to a set of data that is derived from historic waterborne cargo flow data provided by USACE. This chapter is organized as follows: first, it provides an

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introduction to the waterway system and general problem, second elucidates the linear integer models, third introduces designed heuristics and an computer application based on them, and finally displays the obtained results from both exact models and heuristic methods.

### **3.1 Introduction**

Marine transportation including waterways and channels, coastal ports, and locks and dams is a key part of US domestic and international freight transportation. Most of commercial cargo that is moved through coastal ports is foreign imports and exports [47], nonetheless these ports also handle significant amounts of domestic freight transported via short-sea shipping routes. Recently, the waterway transportation system has evoked more attention according to its high efficiency in energy consumption compared with other alternative modes as well as its unique role in promoting international commerce. Due to rising problems on land-side modes like growing congestion, and environmental concerns as well as the growth of fuel prices continue as result of exhausting fossil sources of energy, the tendency and to use waterborne trade routes for domestic freight shipments is improving significantly [48]. However, promoting marine transportation is tightly concerned of the waterways conditions and the draft of waterways. Keeping the adequate draft is possible through the expensive special operation of removing the settled sediments from the channels bed, named as dredging. According to the big size of US marine transportation network and the

insufficient budget for covering all necessary dredging operations cost, there is a competition between different projects and different region to receive the funding.

One of the vital missions of US Army Corps of Engineers is keeping the waterways up to capacity and maintenance of navigable waterways. Thus each year Army Corps removes hundreds of millions of cubic yards (CY) of sediment from navigation channels nationwide in order to maintain projects at authorized dimensions and to provide the safe and cost-effective marine transport. Man-made water channels experience shoaling through natural process of sedimentation that happens when sand and silt carried from downstream by tidal and longshore currents or wave actions gradually fills bottom of channels and harbors. The federal funds for annual Operations and Maintenance (O&M) dredging of coastal projects come from the Harbor Maintenance Trust Fund (HMTF), and amounts of this fund have averaged over \$700 million per year since 2002 [49]. Meanwhile, O&M dredging needs identified by project managers throughout the Corps for HMTF-eligible projects have been in excess of \$1.5B annually, indicating a strictly constrained funding situation from the national level perspective. Therefore, the critical challenge Corps decision makers are facing to is how to optimize the limited HMTF dredging outlays allocation and inland waterway O&M expenditures across the vast waterway network in order to maximize overall benefits or minimize the costs nationwide.

Every year the Corps evaluates navigation projects based on multiple performance metrics indicated in the annual published budget guidance[50]. For Navigation O&M, these metrics include annual total project tons of cargo (5-yr average),

project ton-miles (a measure of tonnage multiplied by the distance traveled within the project), and \$-value of exported cargo (obtained via figures from US Customs), among many others. The Corps' Waterborne Commerce figures show 59 navigation projects in this "high-use" category [51], though the exact number of projects exceeding the arbitrary 10-million-ton threshold may vary somewhat from year to year. This and other port-centric approaches [52] to O&M dredge budgeting treat navigation projects as a portfolio of discrete, independent entities that can be prioritized in a straightforward manner according to one or more performance metrics. After all, in many cases a major percentage of the total transiting freight is also dependent upon the availability of other navigation projects elsewhere within the broader marine transportation system. The project-based approach to budgeting, which gives no added consideration to the cargo that transits multiple navigation projects, can therefore cause resources being assigned to a different list of projects suggested by a systems-based approach[1].

The important fact about programming the maintenance projects on a network is the existence of interdependencies between different projects. That is the maintenance dredging conducted at one project may not bring benefits to the whole transportation system since the projects sending cargo to and/or receiving cargo from that project or other intermediate projects are not also maintained to comparable depths. Subsequently the overall benefits to the waterway transportation system from dredging are a function of a network-wise combination of navigation projects funded for dredging maintenance projects under a given O&M budget plan.



The principal contribution of the material presented in this section is its ability to offer a system-based approach to collectively assess the overall benefits (based on historical tonnage flows) for any combination of proposed O&M dredging work packages. The origin-destination (OD) tonnage data and associated routes for commodity flows between ports are extracted from the Corps' detailed Waterborne Commerce database via the Channel Portfolio Tool [47]. The goal of the model presented in this section is to maximize overall waterway network throughput gains. The mixed integer program (MIP) models used in this work have a large number of binary variables; the formulation is applied to a medium sized problem with about 70 ports, using data from the Great Lakes port system. Then a larger example is also formulated using cargo flow data from roughly 160 navigation projects from both the coastal and inland navigation systems. In addition, six heuristic methods are introduced by using different measures of project performance in order to approximate the optimal combination of funded dredging jobs with less computational effort than the full MIP optimization.

### **3.2 Problem Description and Solution**

This chapter is going to solve i the dredging selection problem could be defined as follows: there are  $N$  navigation projects, each requesting dredging funds in the upcoming budget cycle. Each project  $i$  has a budget request. There is an expected benefit due to both projects  $i$  and  $j$  receiving funding for dredging. This expected benefit may be measured in terms of reduced shipping costs between the two ports, due to vessels being

able to carry more cargo per voyage and take advantage of deeper channel depths. The total budget for all the projects is subject to a ceiling  $B$ . The selection problem is to choose the combination of projects to fund that maximize the total waterway system benefits while complying with the overall budget ceiling,  $B$ .

The commercial ports located along the Great Lakes provide a straightforward example for formulation of dredging selection problem. The ports located along a single lake are connected thoroughly; that is, the benefit  $b_{ij}$  from increased drafts are fully realized if both ports  $i$  and  $j$  are dredged. However, for ports located on two different lakes, one or more connecting rivers (e.g. St. Marys River, St. Clair River, and Detroit River) along the connecting route must also be dredged to comparable depths to allow that  $b_{ij}$  is realized. The numerical examples presented in this chapter are according to detailed Waterborne Commerce cargo flow data among the Great Lakes ports and inland waterways, respectively. Figure 2 represents the Great Lakes navigation system, which is used for the first numerical example.



Figure 2 The Great Lakes ports naturally form a network to support regional commodity flows (USACE Detroit District: <http://www.lre.usace.army.mil/>)[1]

The following notation is used in each example formulation:

$x_{ij}$  = Objective function variable, which is 1 when both port  $i$  and  $j$  and all the other intermediate ports along the route connecting  $i$  to  $j$  are dredged for the improved benefits; 0, otherwise, where  $i \neq j$ ,

$d_i$  = Binary decision variable, which is 1 when port  $i$  is selected to dredge; 0, otherwise ,

$b_{ij}$  = The increase in the throughput between  $i$  and  $j$  gained from dredging both ports  $i$  and  $j$ , based on historical cargo flow at depths to be dredged between ports  $i$  and  $j$ ,  
 $c_j$  = The cost for dredging port  $j$ ,  
 $B$  = The total amount of budget available for dredging projects in present budget cycle,  
 $S(i,j)$  = Set of all projects that are necessary to realize the benefit,  $b_{ij}$ .  $\{i, j\} \in S(i, j)$ . For example, if a flow from  $i$  to  $j$  goes through projects  $i, k, m, j$ ,  $S = \{i, k, m, j\}$ .

Now having identifying the needed variables and parameters to solve dredging selection problem, in the following subsections two approaches are presented for solving this problem. The first approach look for an exact solution through mixed linear-integer models and the second one is a collection of heuristics that look for near optimal solutions in a more efficient computational time.

### 3.2.1 A Mixed Integer Programming (MIP) Formulation

A MIP model, referred to as ORD, is presented as follows:

$$\text{Max} \sum_i \sum_{j < i} b_{ij} \cdot x_{ij} \quad (1.0)$$

*s.t.*

$$x_{ij} \leq d_k \quad \forall i, j: i < j, \text{ and } k \in S(i, j) \quad (1.1)$$

$$\sum_{k \in S(i, j)} d_k \leq x_{ij} + |S(i, j)| - 1 \quad \forall i, j: i < j \quad (1.2)$$

$$\sum_i d_i c_i \leq B \quad (1.3)$$

$$x_{ij} \in R^+ \quad \forall i, j: i < j \quad (1.4)$$

$$d_i \text{ binary} \quad \forall i \quad (1.5)$$

The constraint (1.1) indicates the connectivity condition. It indicates the incidence relationship between  $x_{ij}$  and  $d_k$  where selection of project  $k$  is necessary to realize the benefit  $b_{ij}$ . Constraint (1.1) ensures  $d_k$  is set to 1.0 when  $x_{ij}$  is set to 1.0, which enforces the notion that harnessing the benefits of deeper-drafting shipments between ports  $i$  and  $j$  requires adequate maintenance dredging of all projects along the route from  $i$  to  $j$ . Constraint (1.2) enforces  $x_{ij}$  to 1.0 when each of the  $d_k$  on this route is set to 1.0. Constraint (1.3) is the overall budget constraint, and finally (1.4) and (1.5) are the positivity and binary constraints, respectively.

This binary formulation is appropriate for dredging project selection problem considering this assumption that maintenance dredging work packages submitted by the Corps Districts are either rejected or funded in full. The problem allowing for partial work package funding is investigated in chapter IV . Also note that constraint (1.2) is redundant when the benefit  $b_{ij}$  is positive for all  $i$  and  $j$  because the objective function would ‘force’ the  $x$  variable to be 1.0 for maximization even when (1.2) is absent. However, if  $b_{ij}$  can be negative, a realistic formulation since deferred dredging maintenance often results in additional shoaling and further losses of navigable depth, then constraint (1.2) is required. In the numerical tests presented at the end of this chapter, constraint 1.2 is not included in running the model since the proposed dredging is carried out to increase the depth and  $b_{ij}$  are considered positive, thus constraint 1.2 is not included (cases of negative  $b_{ij}$  due to deferred maintenance dredging will be considered in next chapters). Note that the formulation ORD is a general case of the

traditional formulation that is a quadratic objective function MIP model that proposed by Nemhauser and Ullman [26]. That model eliminates constraints (1.1) and (1.2) and replaces the objective function with if pairwise interaction of projects that results in eliminating variable  $x_{ij}$  and uses  $d_i$  as the only decision variable. The problem that they addressed is a very special case of the waterway network dredging problem presented here.

To consider all the interactions in addition to pairwise interaction, the traditional formulation would have to use big order of nonlinearity terms in the objective function such as  $d_i d_j \dots d_m$  to account for the benefits from dredging projects  $i, j, \dots, m$ . This nonlinearity between multiple projects  $i, j, \dots, m$  cannot be addressed by the approaches in the literature such as. Formulation ORD thus allows consideration of benefits from multiple projects in a linear objective function, which is convenient for taking advantage of commercially available optimization software. In developing program ORD, the following properties have been observed:

**Property 1:**

ORD is a symmetric problem where the symmetry of problem holds following through following condition:

$$x_{ij} = x_{ji} \text{ and } b_{ij} = b_{ji}, \quad \forall i, j$$

In this case, one may only define  $x_{ij}$  where  $i < j$ , in order to reduce the size of the formulation by not considering  $x_{ij}$  for  $i > j$  that results in reduction of the number of  $x$  variables roughly in half. In the case  $b_{ij} \neq b_{ji}$  (perhaps due to flow directionalities), by

making new parameters  $b'_{ij}$  as follows and replacing all  $b$  's with  $b'$  's in ORD

formulation, one may get an ORD formulation that gives an identical optimal solution:

$$b'_{ij} = b'_{ji} = (b_{ij} + b_{ji}) / 2$$

In this case, one needs only define new variables  $x_{ij}$ , where  $i < j$ , with corresponding benefits. The symmetry property allows significant reduction of the size of the ORD formulation and therefore helps expedite the numerical solution. One may also observe the benefit transitivity of the problem. If  $x_{ij}=1$ , and  $x_{jk}=1$ , then  $x_{ik}=1$ , as is dictated by the formulation.

An advantage of having this formulation is that one can simply rely to widely available commercial optimization software such as Cplex, SAS, and Matlab optimization suites for the solution. Note that the formulation is flexible in dealing with some special real-world situations. For example, from port A to port B, assume that there are two separate benefits tabulated based on historical cargo flow trends: one is based on historical cargo volumes traveling directly from port A to B and the other is based on an alternate route via a third waterway project C. That is, there are two routes from A to B:  $A \rightarrow B$  and  $A \rightarrow C \rightarrow B$ . According to the two separate routes, two benefit variables are defined,  $b_{ab1}$  and  $b_{ab2}$  with corresponding decision variables  $x_{ab1}$  and  $x_{ab2}$ , where  $b_{ab1}$  depends on selection (for funding) of projects A and B while  $b_{ab2}$  depends on selection of all the three projects at A, B, and C. Therefore, the resulting terms in the objective function would be:

$$b_{ab1} \cdot x_{ab1} + b_{ab2} \cdot x_{ab2}$$

Likewise, the constraints (1.1) associated with  $x_{ab2}$  may be given as follows:

$$x_{ab2} \leq d_a$$

$$x_{ab2} \leq d_b$$

$$x_{ab2} \leq d_c$$

The constraints (1.1) for  $x_{ab1}$  remain the same as for the normal situation with a single route between ports.

The ORD formulation is a deterministic one that can also be used to approximate instances with uncertainty like the existence of error in the benefit estimate,  $b_{ij}$ . The error in benefit is almost a natural existing error due to many inaccuracies in the derivation and estimation of the benefit as well as many noises that involve. Thus, the actual value of benefit is a random variable  $\beta$  that values in a range like  $(b_{ij} \cdot (1 \pm \alpha_{ij}))$ . Usually the revealed benefit  $b_{ij}$  could be taken as the expected of this random variable:

$$b_{ij} = E[\beta_{ij}] \text{ and } \alpha = (\alpha_{ij})$$

where,  $\alpha$  is usually a small positive number like (0.05, 0.03, ...). The actual formulation of the project selection problem shall use the random parameter in the objective function, denoted as  $ORD(\hat{B})$  whose expected objective value is denoted as

$$E[ORD(\beta)]. \text{ That is, the objective function is } E\left[\sum_{i < j} \sum_j \beta_{ij} x_{ij}\right], \text{ that implies that project}$$

selection maximizes an expected outcome for all possible possibilities of benefit. This formulation then accounts for benefit estimation errors. In addition, we specially denote the formulation that uses  $b_{ij}$  in the objective function by  $ORD(b) = ORD(E(\beta))$  in contrast with  $E(ORD(\beta))$ .



It is worth investigating how program ORD performs in accounting for possible estimation errors in benefits. Next property expresses some fact about the solution of ORD model while the situation is stochastic.

**Property 2:**

According to Jensen's inequality [53], we have the following relationship for convex functions:

$$E(g(X)) \geq g(E(X))$$

which indicates that the expectation of any random function of X, is greater than the value of expectation of X in that function. Thus for concave function, like ORD, the reverse condition holds as:

$$E(g(X)) \leq g(E(X))$$

Subsequently,  $E[\text{ORD}(\mathbf{B})] \leq \text{ORD}(E[\mathbf{B}]) = \text{ORD}(b)$ , where  $b = E(\mathbf{B})$ , which means the objective value from a deterministic solution using the expected benefit  $b_{ij}$  provides an upper bound to the maximum possibly achievable benefit that results from optimally solving each instance of  $\beta$ . Regarding the error term, for each specific instance of  $\mathbf{B}$ , the expectation over the objective value of  $\text{ORD}(\mathbf{B})$  using the solution  $(b^*, x^*)$  from  $\text{ORD}(b)$  is less than the objective value of  $\text{ORD}(\mathbf{B})$  by no more than

$$\sum_{i < j} \sum_j \alpha_{ij} b_{ij} x_{ij}.$$

Therefore, Property 2 provides a convenient way to estimate the loss from using a deterministic formulation to solve a practical problem with random errors in the benefit estimates. The errors may be project specific, or may also be a constant adjustment value across the board based on some overall assessment of the data quality by the decision makers.

### 3.2.2 A Proxy Model for ORD

In this section, a proxy formulation (referred to as PorD) is proposed as an approximate alternative to Program ORD above. The purpose of providing this proxy model is to improve the solution speed via tightening feasible solution by a bit sacrificing from the model accuracy. The proxy model is developed as following:

$$\text{Max} \sum_{i < j} \sum_j b_{ij} x_{ij} \quad (2.0)$$

*s.t.*

$$x_{ij} \leq d_k + d_m - 1 \quad \forall i, j : i < j; k, m \in S(i, j) \quad (2.1)$$

$$\sum_{k \in S(i, j)} d_k \leq x_{ij} + |S(i, j)| - 1 \quad \forall i, j : i < j \quad (2.2)$$

$$\sum_i d_i c_i \leq B \quad (2.3)$$

$$x_{ij} \in R \quad \forall i, j : i < j \quad (2.4)$$

$$d_i \text{ binary} \quad \forall i \quad (2.5)$$

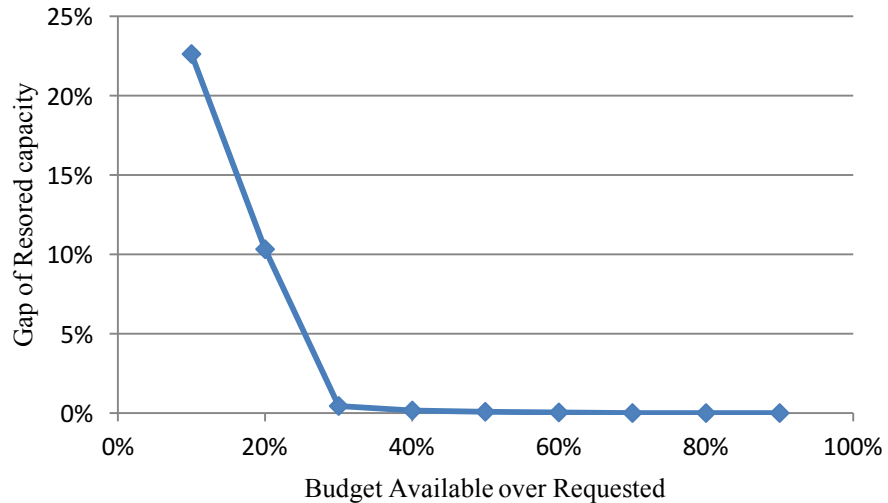
This enhanced proxy formulation is proposed because of an observation that when each  $d_k$  is fractional, constraints (1.1) and (1.2) are both loose in ‘forcing’  $x_{ij}$  to be

binary. For example, if  $d_i$  and  $d_j$  are 0.5 and 0.6 respectively in the LP solution, ORD would allow  $x_{ij}$  to be as large as 0.5 while PorD would ‘force’  $x_{ij}$  to be no larger than 0.1: the ‘actual’ benefit harnessed from having a fractional solution through LP relaxation of PorD is smaller than with ORD.

**Property 3:**

Constraint (2.1) is a valid cut to Constraints (1.1) through (1.3). As one may see, when each  $d_k$  is fractional, a solution to (2.1) satisfies both (1.1) and (1.2). Therefore, we can reasonably say Constraint (2.1) is significantly tighter than (1.1). However, (2.1) also makes it possible for  $x_{ij}$  to be -1.0 when the corresponding variables  $d_k$  and  $d_m$  are both 0, which alters the problem formulation from program ORD in terms of the objective value. This proxy formulation equivalently “rewards” the benefits due to shipping between two ports, each having a project selected, neutralizes the benefits from shipping between two ports if only one project is selected, and effectively penalizes the benefits between two ports if no projects are selected. Computational tests in 150 randomly generated instances were conducted based on the actual Waterborne Commerce cargo flow data for the Great Lakes by uniformly varying the benefits and project costs by  $\pm 50\%$  for all the navigation projects. These numerical tests show that when the budget constraint is at least 30% of the total requested, PorD yields a solution identical to that from ORD. As the budget constraint is tightened (below 30%), ORD provides greater restored system benefits than does PorD, but the difference generally remains within a

range of 25%. Figure 3 shows the average difference between total restored system benefits from ORD and PorD.



**Figure 3 Average optimality gap of restored system capacity from using ORD and PorD [1]**

Despite the simplification presented by Property 3, PorD on average requires more computational time than ORD, presumably because PorD has more constraints. For the Great Lakes ports example with 70 navigation projects, both ORD and PorD have comparable computational performance. However, for larger problems such as the expanded example covering both coastal and inland river ports, ORD requires less computational time because PorD has significantly more constraints. Nonetheless, the formulation PorD is kept here because it offers a slightly different consideration in

practice and provides some complementary insights to ORD, along with comparable computational efficiency for many practical problems.

### **3.3 Heuristic Approaches**

The MIP formulations can effectively lead to optimal solutions for small and medium-sized problems through the use of commercial optimization software. In numerical tests performed over the course of this study, the MIP formulations have successfully solved practical problems such as the port dredging projects for the Great Lakes region.

However, the lack of a polynomial time guarantee for the MIP formulation presents potential challenges with expanding the approach to cover, for example, the entire USACE dredging project portfolio. A polynomial time heuristic, in contrast to the full MIP formulation, possesses great practical advantages, and can, among other benefits, expedite the process of conducting sensitivity analysis to impart new knowledge to decision makers concerning aspects of navigation system performance. In addition, heuristic methods often do not rely on commercial software such as CPLEX<sup>®</sup> or MATLAB<sup>®</sup> and can be standalone and easy to implement. An additional motivation for an efficient heuristic method is that a quality feasible solution may provide a tight bound to the MIP formulation to expedite the branch and bound (B&B) process for the optimal solution.

The proposed heuristic process rank orders navigation projects according to a certain criterion, and then selects projects to fund based on their position above or below the budget-driven cutoff line. The process could be described formally as follows:

- *Step 1*: rank order the candidate projects according to a pre-determined criterion.
- *Step 2*: Consider the first project that has not yet been considered going down from the top of the rank-ordered list. If the project fits within the remaining budget, select it for funding and update the remaining budget by deducting the new selected project cost. If the project does not fit within the remaining budget, go to Step 3.
- *Step 3*: *Stop* if no projects remain unconsidered on the rank-ordered list, or if no remaining budget is available; otherwise, repeat Step 2.

Four alternative ranking criteria are proposed, each of which is a project-specific metric defined by considering the network effect in a particular way. Historical Waterborne Commerce data (annual tonnage exchanged between navigation projects at depths to be dredged, and associated routes) are used as benefit  $b_{ij}$  obtained from dredging projects  $i$  and  $j$ . Specifically, historical annual tonnage totals utilizing the deepest, shoal-vulnerable depths of navigation channels are used to provide relative estimates of the benefits of dredging a particular combination of projects. Heuristics 1, 2 and 3 result accordingly. Heuristic 1 attributes half of the tabulated tonnage, including through and local traffic, to a relevant port in calculating the project performance metric. Heuristic 2 calculates the total benefit as the sum of all tonnage that depends on the port of interest over the total cost of projects which also share the traffic going through that particular port. Heuristic 2 considers a benefit as resulting from investment at all ports along an OD route in calculating the ratio. Heuristic 3 uses the total benefit allotted to a port proportionally to the total project cost, a ‘wild’ heuristic.

In addition, heuristics 4 and 5 are proposed to dynamically apply other criteria. Heuristic 4 dynamically applies the ranking criterion in Heuristic 2 while Heuristic 5 dynamically applies a criterion as specified in Table 1. The dynamic process is to re-rank the remaining projects each time after a project is selected to fund. The dynamic process is embedded in the three step process described above. The funded projects are excluded from consideration in calculating the ranking criteria subsequently in step 2.

Heuristic 6 selects the solution with the highest restored benefits from heuristics 1 through 5. The six heuristics are presented in Table 1. Note that in calculating the ranking criterion, heuristics 1 through 5 all imply an assumption that remaining projects will be funded. There is room for further improvement by dynamically adjusting the weight for each remaining project based on its likelihood of being selected, which is beyond the discussion here. These heuristics work optimally in several special cases as follows:

Case 1: Decomposable pair-wise correlated projects. This case has isolated shipping routes, each route going through two projects. These pairs of projects have no interaction with each other. In this case, heuristics 2, 4, and 5 all solve the problem to optimum.

Case 2: star-structured network of projects. This is a hub and spoke structured network. Each project has a benefit dependent partially on a 'hub' project. In this case, heuristics 1 and 3.

Real-world waterway network problems are almost impossible to transform into either of the two distinct structures above. For example, for the Great Lakes example with 70 ports/projects, there is a tremendous degree of interconnectedness, with most

ports both sending cargo to and receiving cargo from several other ports in the system. .

However, depending on the relative magnitude of costs and benefits, each example might be approximated by one of the two structures or by a combination of the two structures above. The accuracy of such an approximation may be indicated by the optimality gap of the heuristic solution relative to the MIP solution.

**Table 1 Criteria for heuristic measures and other indices [1]**

Heuristic	Performance Ratio or other criteria for project k
1	$\frac{\sum_{(i,j):k \in S(i,j)} b_{ij}}{2c_k}$
2	$\frac{\sum_{(i,j):k \in S(i,j)} b_{ij}}{c_k + \sum_{(i,j):k \in S(i,j), i \neq k, j \neq k} (c_i + c_j)}$
3	$\frac{c_k \cdot \sum_{(i,j):k \in S(i,j)} b_{ij}}{(c_k + \sum_{\substack{m \neq k \\ m, k \in S(i,j)}} c_m)}$
4*	Dynamic H2
5*	Dynamic $\sum_{(i,j):k \in S(i,j)} \frac{b_{ij}}{\sum_{m \in S(i,j)} c_m}$
6	$MAX \{H1, H2, \dots, H6\}$



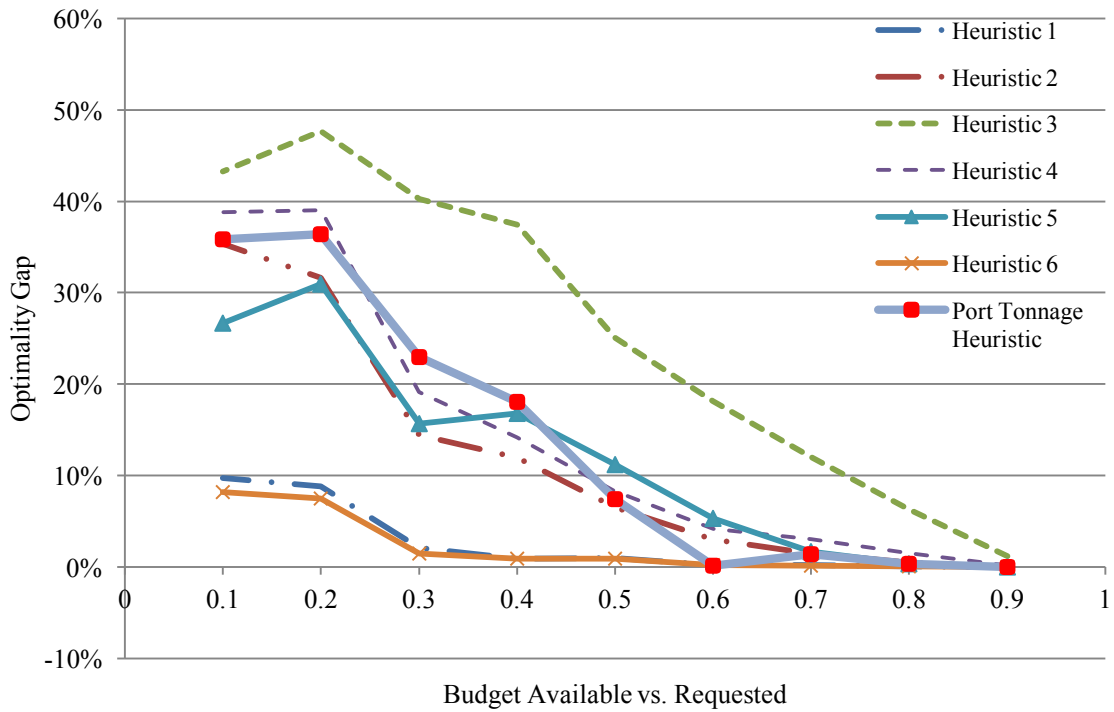
### 3.4 Numerical Results

To evaluate the performance of models and algorithms described above, some numerical tests are conducted in this study. Two real world networks are taken in numerical tests, the first is based on a set of 70 navigation projects at ports along the Great Lakes. The second network is carried out on a larger port system with 159 dredging projects from coastal ports as well as the inland waterways such as the Mississippi River, Ohio River, and Gulf Intracoastal Waterway. Again, origin-destination commodity flows cause project performances in terms of throughput to be correlated. This example is significantly larger than the Great Lakes network in terms of the number of decision variables and constraints in the ORD and PorD.

The benefits are calculated based on the historic tonnage flows passing between respective ports at depths to be restored by the proposed maintenance dredging projects. In order to infer system-wide dredging priorities (i.e. most critical portions of the navigation system), the sensitivity analysis is conducted wherein the overall budget constraint is varied as a percentage of the sum of all requested funding amounts. The MIP programs and the heuristics are all applied to each resulting hypothetical budget scenario. In addition, tonnage and dredging cost data for the Great Lakes port projects were varied from their real-world values in order to test the performance robustness of the algorithms across a greater spectrum. For each budget scenario indicated by the ratio between budget available and budget requested, 150 instances were generated for the Great Lakes example by randomly varying the benefit for each path between an origin/destination pair, and randomly varying the project cost. The percentage of

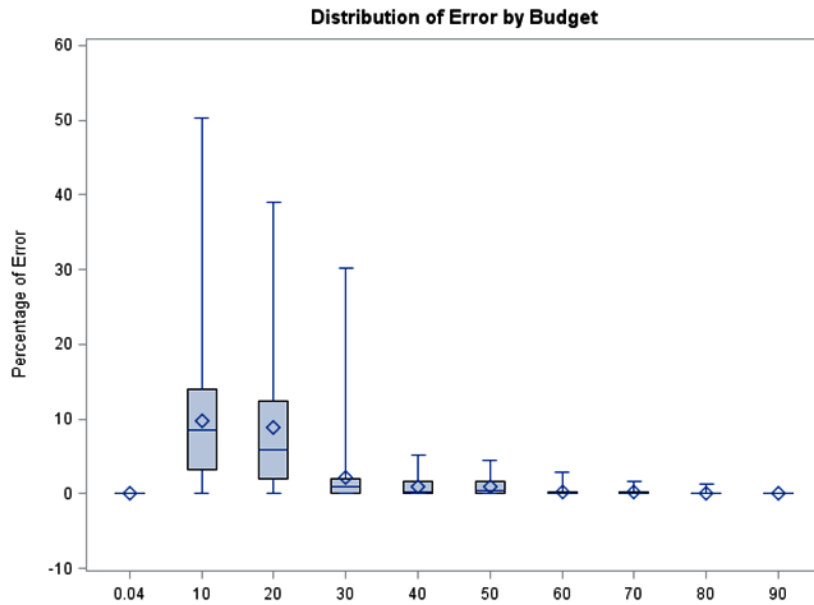
variation is uniformly randomly generated between -50% and 50% based on the actual data for each instance.

The optimal solution and the heuristics are applied to each of these 150 instances in a given budget scenario. Figure 4 summarizes the average optimality gap between the heuristics and optimal model for each budget scenario. A curve labeled "Port Tonnage Heuristic" is also included to show the optimality gap when projects are rank ordered according to total tonnage without considering dredging costs. All heuristic measures except for Heuristic 3 lead to solutions within 10% of the optimum once the budget constraint is more than about 55% of the total requested funding. Heuristic 1 outperforms the other heuristics on the average in terms of optimality.



**Figure 4 The Average optimality gap of heuristics for 70 great lakes ports data [1]**

Figure 5 further illustrates the variance of the optimality gap over the 150 artificial instances for Heuristic 1. Each vertical bar represents the full range of observed optimality gaps, the shaded blue rectangles represent the 25th to 75th percentiles of all observed optimality gaps, and the mean is indicated by the diamond markers.

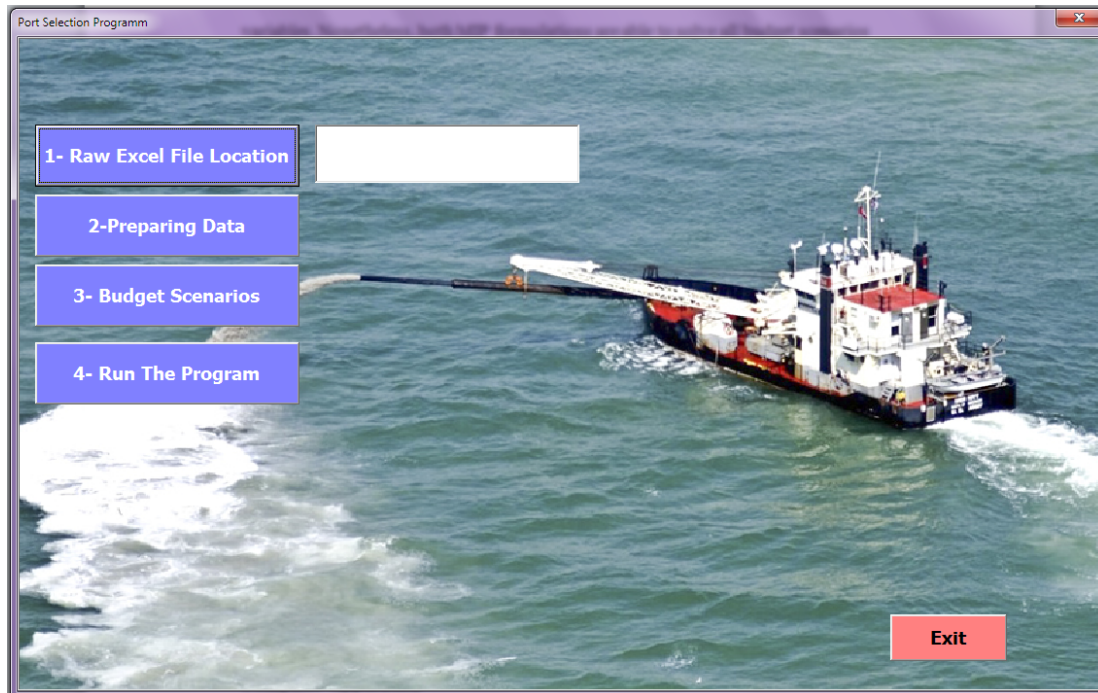


**Figure 5 Variance of optimality gaps with budget for heuristic 1 over 150 instances [1]**

In case of inland waterways example, the nature of project interdependencies is significantly different, in accordance to the network topology of this system and the prevalence of "thru" traffic in most sections of river. With the 159 port/river projects, the ORD and PorD formulations approximately have 21,392 and 72,370 constraints, respectively and 3,471 decision variables. Nonetheless, both MIP formulations are able to solve all budget scenarios within about 10 seconds. Figure 5 shows the optimality gap for each heuristic measure as well as for the Port Tonnage Heuristic for a single instance of costs and benefits (based on historical data) for the larger coastal and inland projects example. It is interesting to note that in spite of the differing network topology, the relative performance of the various heuristic measures is similar to that for the Great Lakes example, with Heuristic 1 outperforming all others.

### 3.5 Computer Application

A user interface application is designed according to the heuristic methods. Figure represents a snap shot of this application. This application facilitate running the heuristic methods on waterway network of big sizes. In addition to the simplicity and time efficiency of heuristic models, the possibility of using this application on any computer and removing the need for a specific software programming packages, makes it a powerful tool especially for real time general decision making. Figure 6 presents a snapshot of designed program for running the heuristic method.



**Figure 6 Snapshot from the developed application to find the optimal dredging location according to developed heuristic methods**

## CHAPTER IV\*

### CONTINUOUS DREDGING MODEL

This section introduces the fund allocation problem for dredging and other maintenance project that allows for partial funding and therefore partial benefit of each project. The model presented is an integer programming formulation that enables the funding level of each project in a continuous range from 0 to 1 with 0 being no funding at all and 1 being fully funded as requested. Partial benefit results accordingly from partial funding that allows for selecting an action among a range of possible actions (dredging depth). We refer to model in this chapter as continuous model to differentiate with the binary decision model developed in chapter III. Continuous model opens the window for further presented probabilistic model where it is needed to study the shoaling as a phenomenon that partially influence the benefit of waterway system.

#### **4.1 Problem Definition**

This study considers a network comprised of waterway segments represented by a set of nodes and a set of links. Each link may be construed as an entity with a through capacity for cargo movements. For example, a link on the abstract network may be for a lock/dam or a section of river. Nodes are for the beginnings and endings of links or connections between links. Commodities travel between origins/destinations, referred to as OD flows

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as typical in literature. Each origin or destination is just a point on the network. Each OD flow goes through the network along a specific path that consists of a set of connected links. For convenience of presentation, dams/locks, ports and river segments are referred as elements of the infrastructure system. One may find that each link on the study network corresponds to a physical element of the system. Each element has a capacity that can be improved, and the magnitude of that improvement is determined by extent of the maintenance action taken. Similarly, the maintenance cost for each element is also a function of the extent of the maintenance action. Each year, there is a set of maintenance requests, each having a fixed budget and an improvement to capacity of the according elements. The network has a limit to the maintenance budget ( $B$ ) each year for all the maintenance requests proposed for the same year. Each maintenance request has a requested budget and an expected improvement to the elements in terms of dredging depth (to rivers or ports). To simplify the problem, we unify the improvement to elements by using a measure of improved throughput capacity. In this part of research, it is allowed to consider partial funding assignment to a project request in order to harness the full potential of this optimization problem. Partial funding results in partial benefits accordingly. The objective of this resulting model is to select maintenance projects in order to maximize the total network OD flow.

## **4.2 A Project Selection Model**

This section presents the developed model to solve the above described problem. The model is a mixed linear integer one that allows partial funding of a project, which is

named as continuous dredging program (CDP). The used notation for this problem are as follows:

- Variables:

$d_{ij}$ : The depth of dredging for a river segment/link between node  $i$  and  $j$  (feet). This depth is a non-negative real number that has a value of zero if  $(i,j)$  is a rail/highway segment.

$f_{ij}$ : The tonnage flow accommodated on the network out from origin  $i$  to destination  $j$ .

$x_{ij}$ : Total commodity tonnage flow after project implementation on link  $(i,j)$  (tons).

- Parameters:

$q$ : The amount of increase in waterway available capacity resulting from one unit increase (tons/ft) in draft due to dredging.

$c_{ij}$ : Cost of a unit depth of dredging for waterway segment/link between node  $i$  and  $j$  (\$/ft).

$g_{ij}$ : The capacity of link  $(i,j)$  that represents loading/unloading capacity at a dock.

$s_{ij}$ : Current availability of segment from node  $i$  to  $j$  before maintenance projects (tons).

$\varphi_{ij}$ : The weight for OD flow from  $i$  to  $j$ , that may be the distance of that flow so that the total mileage value is maximized.

B: Total budget available for maintenance projects (\$).

E: The set of links of the network including links for locks/dams and links for river segments and road sections.



L: Set of all loading and unloading segments.

OD: Set of all origin or destination pairs.

$D_{ij}$ : Demand of commodity to be shipped from origin  $i$  to destination  $j$  (tons).

$I(i, j)$ : Set of all itineraries of freight that traverse link  $(i, j)$ .

$S(i, j)$ : Set of all segments that consist the route connecting origin  $i$  to destination  $j$  to realize the benefit,  $b_{ij}$ . For example, if a flow from node  $i$  to node  $j$  goes through nodes  $i, k, m, j$ ,  $S = \{(i, k), (k, m), (m, j)\}$ .

The proposed formulation CDP is presented as follows:

$$Max \sum_i \sum_j \varphi_{ij} f_{ij} \quad (3.0)$$

s.t.

$$x_{ij} \leq s_{ij} + d_{ij} \cdot q \quad \forall (i, j) \in E \setminus \Omega \quad (3.1)$$

$$\sum_{(i, j) \in E \setminus \Omega} c_{ij} d_{ij} \leq B \quad (3.2)$$

$$x_{ij} \leq g_{ij} \quad \forall (i, j) \in L \quad (3.3)$$

$$x_{ij} = \sum_{mn \in I(i, j)} f_{mn} \quad \forall (i, j) \in E \quad (3.4)$$

$$f_{ij} \leq D_{ij} \quad \forall (i, j) \in OD \quad (3.5)$$

$$x_{ij}, f_{ij} \geq 0 \quad \forall i, j \quad (3.6)$$

$$d_{ij} : Integer \quad \forall i, j \quad (3.7)$$

The objective function aims to maximize the total value of all OD flows accommodated by the system capacity. Coefficient  $\phi_{ij}$  is a weight factor to OD flows. The weight factor would allow consideration of commodity values and distances. If it takes the form of the distance of an OD flow, the objective would maximize the total ton-mileage on the network. And if it takes the unit value of commodities according to groups, the objective would maximize the total commodity value shipped on the system. Constraint (3.1) dictates that the OD flows accommodated cannot exceed the link capacities. The link capacity consists of existing capacity and expected increase of capacity due to maintenance.

Constraint (3.2) ensures the total budget constraint. Constraint (3.3) is designed for the loading/unloading docks. On the network, we have directional links for loading and unloading docks respectively. In this case,  $g_{ij}$  represents the loading and unloading capacity. Constraint (3.4) represents that the flow on each link is sum of all paths' flows routing through that link.

Constraint (3.5) rules that the accommodated OD volume be less than the OD demand. Constraints (3.6) and (3.7) are non-negativity and integrality constraints.

It is worth mentioning that even though CDP is developed based on aggregated commodity flow data, it could be modified to explicitly consider commodity by groups such as bulk cargo and manufactured goods by defining new variables  $f_{ij}^k$  and  $D_{ij}^k$  with the superscript  $k$  being the commodity group and minor additional changes to the formulation. It is noteworthy that the proposed model has the capacity of an intermodal

model corresponding to the constraint (3.3). This constraint indeed, is reflecting the dependency of waterway system expansion on the availability of landside modes. In other words, to have an effective maintenance, a reasonable model should also see the connection of waterways to landside modes and if there is enough room for added throughput invoked by waterway improvement. Constraint (3.3) represents this connection, however a more detailed model that takes account of a multi modal network would be presented in chapter IV.

### **4.3 Simplified Dredging Model**

Since the problem of a multimodal network is being investigated in more detailed in chapter 6, the CDP model is adjusted in order to only account for partial funding on dredging maintenance problem. Thus, CDP is simplified a bit and a proxy to CDP is presented in this section that neglect the possible relations to landside. This simplified model only considers the river segments and ports as the elements of network and does not consider the relation of these element with the other components like locks/dams and landside transportation modes. In addition, due to the waterborne freight data being organized into 1-ft vessel draft increments as well as inherent challenges in carrying out channel maintenance dredging to within 1-ft accuracy, the model is modified to account for costs and benefits and 1-ft increments of channel depth.

To summarize, two assumptions are considered within the model CDP:

It is assumed that demand is large enough to dominate the sum of flows between each origin destination pair. Therefore, constraint (3.4) can be ignored. This assumption

simply means that the model will maximize the overall shipping potential capacity on the system with an equal weight on all the possible OD pairs.

Dredging depth can only be an integer number. A new binary variable  $y_{ij}^k$  is introduced. Variable  $y_{ij}^k$  is one when the all the segments along origin  $i$  and destination  $j$  have a dredging depth of  $k$  ft; and is zero otherwise. With the introduction of  $y_{ij}^k$ , the objective function (3.0) changes to  $Max \sum_i \sum_j \sum_k \varphi_{ij} y_{ij}^k q_{ij}^k$ , where  $q_{ij}^k$  means added tonnage capacity for dredging depth  $k$  along a path from  $i$  to  $j$ . Making  $b_{ij}^k = \varphi_{ij} q_{ij}^k$  a new objective function as  $Max \sum_i \sum_{j < i} \sum_k b_{ij}^k y_{ij}^k$  comes to play.

The revised model is named as CORD, which follows as below.

$$Max \sum_i \sum_{j < i} \sum_k b_{ij}^k y_{ij}^k \quad (4.0)$$

s.t.

$$y_{mn}^k k \leq \sum_l d_{ij}^l l \quad \forall k, m, n: m < n, \text{ and } (i, j) \in S(m, n) \quad (4.1)$$

$$\sum_i \sum_j \sum_k d_{ij}^k c_{ij}^k \leq B \quad (i, j) \in E, j: i < j \quad (4.2)$$

$$\sum_k d_{ij}^k \leq 1 \quad \forall i, j: (i, j) \in E, i < j \quad (4.3)$$

$$\sum_k y_{ij}^k \leq 1 \quad \forall i, j: (i, j) \in OD, i < j \quad (4.4)$$

$$y_{ij}^k, d_{ij}^k \text{ Integer} \quad \forall i, j, k \quad (4.5)$$

where:

$b_{ij}^k$ : Realized benefit due to the increased draft  $k$  between origin  $i$  and destination  $j$ . Note that in numerical test, we adopt the added tonnage capacity as this benefit.

$c_{ij}^k$ : Cost for dredging port lying on segment  $(i,j)$ .

$d_{ij}^k$ : Binary decision variable, which is 1 when segment  $(i,j)$  (a port or a river section) is selected to dredge for depth  $k$ ; 0, otherwise.

$y_{ij}^k$ : Binary variable, which is 1 when all the segments along the path connecting origin  $i$  to destination  $j$  are dredged for a depth maximum consistent depth  $k$ ; 0, otherwise. A maximum consistent depth is the maximum increased depth along a path (some segments may have a draft increase than the maximum consistent depth though).

Objective function (4.0) maximizes the total weighted benefit. Constraints (4.1) ensure that a path depth should be no more than that of each segment along that path. Constraint (4.2) is the budget constraint. Constraints (4.3) and (4.4) describes that each segment and path have only one dredging depth selected. Here, CORD removes all of the constraints on locks/dams and land side transportation of CDP that represent the multimodal network relation. The model only considers the dredging decisions as improvement actions.

Equation (4.1) has a large number of constraints. They are replaced by the following:

$$\sum_k y_{mn}^k k \leq \sum_k d_{ij}^k k \quad \forall m,n:m < n, \text{ and } (i,j) \in S(m,n) \quad (4.1-b)$$

Although this new constraint becomes looser, it decreases the total constraints by a large number. Numerical tests show a significant reduction in solution time by as large as 97 percent. Therefore, constraint (4.1) is substituted by (4.1-b) in CORD program.

## CHAPTER V\*

### PROBABILISTIC DREDGING MODEL

This chapter considers the dredging problem under the stochastic shoaling condition. The models proposed so far are capable of determining the optimal maintenance scenarios when the problem is defined as a one stage decision making without consideration of afterwards situation. However, in the waterway system every segment is under the influence of shoaling even after the dredging. Dredging only changes the distribution of the draft on a segment and increases the expected draft of the segment during maintenance period. The shoaling is completely a random effect that influences waterway systems and the draft of channels. Accordingly, modeling the dredging problem without accounting for the probabilistic shoaling is not quite analogous to the real problem. In this chapter, the previous models are improved to be capable of capturing the shoaling effect in some sense. To this end, the remaining of this chapter is divided in two subsections. The first proposes a deterministic proxy approach to take into account the shoaling effect, and the second uses a promising method in stochastic programming called Sample Average Approximation (SAA) to consider the shoaling effects.

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## **5.1 Deterministic Approximation**

The benefits of dredging a particular waterway segment in the CDP model depends on the depth to which the segment is dredged. In calculating the benefits, one has to consider the loss of draft due to subsequent shoaling. The shoaling depends upon many localized factors such as geological conditions, land-use patterns in the accompanying watershed, recent levels of precipitation in the watershed, and occurrence of coastal storms. All these localized factors are uncertain, therefore potentially resulting in a probabilistic shoaling process at each project location. However, in general, the deeper segments of waterway will be more prone to future shoaling and will lose depth at a faster rate than shallower portions of a channel. Due to the highly complex environmental forces that influence shoaling and inherently random conditions, shoaling can be treated as a random process.

Indeed, the optimal decision that only considers one-year maintenance would be different from programming over several periods. The optimization problem, considering the random shoaling, is in fact a probabilistic integer programming problem with rich literature. However, the challenge with the probabilistic approach is due to the large size of this optimization problem. Considering the large size with many thousands of variables and constraints, the decision was made to resort to deterministic approaches for approximate solutions. This is achieved through using an approximate benefit estimate that considers shoaling in the year after dredging. Clearly, the optimal dredging decision would be dependent on the resulting shoaling probability of the restored new depth.



This chapter presents a model that tries to capture the random shoaling effects called PORD. PORD has the following objective function:

$$Max \sum_i \sum_{j<i} \sum_k b_{ij}^k y_{ij}^k + \sum_i \sum_{j<i} E_{\xi} Q_i(y_{ij}, \xi) \quad \text{PORD (objective function)} \quad (5)$$

where the first term accounts for benefits in the project period, which is the same as that in ORD;  $E_{\xi} Q_i(y, \xi)$  is the expected system benefit over the maintenance horizon after the project period (year one), and  $\xi$  is the realization of a specific dredging depth during the planning horizon after the project year.

This objective function maximizes the expected benefits over the planning period for the maintenance (e.g. the project year and one year after). The test later only considers the year of maintenance and one year after the maintenance, however the approach can easily be extended to include additional years in the planning horizon. The expectation considers the probabilistic shoaling and reduction in draft. Noteworthy, the do-nothing ‘project’ may also lead to a negative shoaling effect that can be modeled in the formulation as well.

In a discrete case, the expected increase of draft in the next year after dredging, compared with the draft before the maintenance, may be described as follows:

$$E_{\xi} Q_i(y_{ij}, \xi) \approx \sum_k z_{ij}^k \varphi_{ij} \sum_{d=0}^k d P^k(\xi = d) \quad (6)$$

where,  $z_{ij}^k$  is a new decision variable that is similar to  $y_{ij}^k$  but is an indicator for the expected depth on the route from node  $i$  to node  $j$  in the second year. It is equal to 1 when depth  $k$  is less than or equal to the expected depth of all the segments along the

path connecting  $i$  to  $j$ ; and is 0 otherwise.  $P^k(\xi)$  is the probability distribution of a segment with depth of  $k$  remaining draft in the period after project year, the domain of which is a set of integer values from 0 to the current existing depth,  $k$ . Here  $\varphi_{ij}$ , as in the CDP model, is the benefit of one unit of dredging between  $i$  and  $j$ . Introducing the new variable  $z_{ij}^k$  requires additional constraints similar to (2-1b) and (2-4). One may set

$b_{ij}^k = \varphi_{ij} \sum_{d=0}^k d P^k(\xi = d)$ . The model with the modified PORD objective function that we

refer as MPORD may be presented as follows.

$$Max \sum_i \sum_{j < i} \sum_k y_{ij}^k b_{ij}^k + \sum_i \sum_{j < i} \sum_k z_{ij}^k b_{ij}^k \quad (\text{MPORD}) \quad (7.0)$$

s.t.

$$\sum_k y_{mn}^k k \leq \sum_k d_{ij}^k k \quad \forall m, n: m < n, \text{ and } (i, j) \in S(m, n) \quad (7.1)$$

$$\sum_k z_{mn}^k k \leq \sum_k d_{ij}^k E_{\xi}(k) \quad \forall m, n: m < n, \text{ and } (i, j) \in S(m, n) \quad (7.2)$$

$$\sum_i \sum_j \sum_k d_{ij}^k c_{ij}^k \leq B \quad (7.3)$$

$$\sum_k d_{ij}^k = 1 \quad \forall i, j: i < j \quad (7.4)$$

$$\sum_k y_{ij}^k = 1 \quad \forall i, j: i < j \quad (7.5)$$

$$\sum_l z_{ij}^l = 1 \quad \forall i, j: i < j \quad (7.6)$$

$$y_{ij}^k, z_{ij}^k, d_{ij}^k \text{ Integer} \quad \forall i, j \quad (7.7)$$

Again,  $b_{ij}^k$  is the benefit of depth  $k$  of dredging between  $i$  and  $j$ . The variable  $z_{ij}^k$  is the decision variable that decides the expected depth of each path in the period after the project planning year. Constraint (3.1) prescribes that draft increase along a path must be no more than the draft increase at each segment of that path waterway path. Constraint (3.2) is similar to constraint (3.1) but for the second year. Constraints (3.4) and (3.5) have changed to equality compared to their counterparts (2.3) and (2.4). Therefore, MPORD can consider the negative benefit of losing depth due to shoaling in excess of the depth gained via dredging or zero benefit when shoaling returns the channel to the same depth from prior to dredging. Subsequently, negative and zero drafts could all be options of expected depth, therefore considering all the situations those constraints sums up to 1.

### *5.1.1 Application of MPORD Model on Great Lakes*

After developing the PORD, it was tested on the Great Lakes example in 9 budget scenarios and its result are compared with the result from ORD where does not consider the probabilistic shoaling. First, to run the PORD, the probability distribution of shoaling for different drafts must be known. Using historical data, we extracted the shoaling probability distribution in a certain period after implementing the dredging as is displayed in Table 2.

**Table 2 The shoaling probability based on historical records**

Dredging Depth (ft)	Depth Loss (ft)					
	0	1	2	3	4	5
0	0.09	0.2	0.35	0.25	0.1	0.01
1	0.06	0.15	0.33	0.32	0.12	0.02
2	0.04	0.12	0.35	0.34	0.13	0.02
3	0.02	0.08	0.34	0.38	0.15	0.03
4	0.01	0.04	0.3	0.4	0.2	0.05

According to table 2, if a segment is dredged for 4 ft, this segment will experience shoaling of of 5, 4, 3, 2, 1, and 0 ft with probabilities of 5, 20, 40, 30, 4 and 1 percent respectively. In other words, if we add the draft of a segment with 4 ft dredging, the expected remained draft of that segment at the end of maintenance period would be:

$$E(\text{Remaining Draft After Shoaling}) =$$

$$(-1 \times 0.05 + 0 \times 0.2 + 1 \times 0.4 + 2 \times 0.3 + 3 \times 0.04 + 4 \times 0.01) = 1.11 \text{ ft}$$

Using the shoaling probabilities in table 2, we obtained the result of MPORD model as presented in Table 3. In this example it is assumed that the shoaling happens one year after dredging operation, and even though the maintenance period is one-year long, we aim to minimize the effect of shoaling for next year to reduce its associated demanded budget. The benefits therein are calculated using the objective function of MPORD model for a two year period. The results displayed for MPORD, represent the optimal total benefit for two consecutive years, assuming the expected shoaling effect for the next year is known. Note that the ORD model does not consider shoaling, and it maximizes the benefit only for the project year then the value in Table 3 is the sum of

ORD objective for first year and the system’s benefit in second year given the expected remaining draft.

**Table 3 Total benefits of ORD and MPORD models on the great lakes network**

Scenario Model	90%	80%	70%	60%	50%	40%	30%	20%	10%
PORD (Kilotons)	96,083	95,363	92,326	86,910	79,275	60,909	40,895	1,930	-8,382
ORD (Kilotons)	96,080	95,201	88,896	84,882	79,060	54,492	37,734	848	-10,410
Gap (%)	0.00	0.17	3.72	2.33	0.27	10.54	7.73	56.08	24.20

Table 3 shows that although the total benefit from MPORD is slightly better than ORD for first five scenarios with more budget available, it produces considerably better solutions for later scenarios where the available budget gets more limited. This closeness could be due to the specific structure of the OD benefits. Often path remains unchanged and does not vary with draft change. The mild shoaling does not bring significant change to the ORD solution. Besides, the negative number that could be seen for the last scenario is due to the negative benefit considered for 0 depth of dredging. This model is flexible to adopt any value for as the benefit of projects.

## **5.2 The Sample Average Approximation (SAA)**

Even though the model provided in previous subsection shows improvement of solutions over the base model, still is a deterministic proxy of the dredging problem with

stochastic shoaling that is not able to fully understand the stochastic nature of the problem and result in conservative solutions. Thus, a methodology with an innate stochastic behavior could improve the solution and comply better with the stochastic setup of the problem. After a comprehensive search inside the literature of the stochastic optimization considering that our problem is specific form of knapsack, Sample Average Approximation (SAA) as proposed by [54, 55] was found to be the most appropriate method for solving our problem. In continuous of this section, first an introduction is provided about SAA and then the result of its application on Great Lakes is presented at the end.

### 5.2.1 Introduction to SAA Concepts

The stochastic dredging problem as displayed in Equation (5) is a type of a two-stage stochastic problems in which the initial decision is made to optimize the objective function in first period plus the expected objective function of second period due to initial decisions and random effects. The optimal solution of the problem then should be decided based on their direct outcome in first stage and their indirect effects in the second stage. The true objective function for the problem could be written as Equation (8).

$$g(x) = f_1(x) + E_{\xi} f_2(x, \xi) \quad (8)$$

where  $\xi$  is a random vector,  $x$  is our decision variable, and  $f_2(x, \xi)$  is a real valued function of two variables  $x$  and  $\xi$ . To calculate the expectation we need to have all the

realizations of  $\xi$  that leaves us with a significantly humongous, though finite set of feasible solutions that grows exponentially and makes the enumeration impossible. In addition, the Equation (8) could not be written in the closed form. To overcome these difficulties, a SAA method was used that is a form of Monte-Carlo simulation method. Sample average of  $f_2(x, \xi)$  replaces the expectation  $E_\xi f_2(x, \xi)$ . The sample average that is an approximation for the equation 8, is displayed in Equation 9:

$$\hat{g}_N(x) = f_1(x) + \frac{1}{N} \sum_{i=1}^N f_2(x, \xi_i) \quad (9)$$

where  $\xi_i, i = 1, 2, \dots, N$  are the observed samples that could be generated with the knowledge of their distribution. First observation about equation 8 and 9 is described as fact 1 where the expectation of sample average is equal to true objective function of the problem:

*Fact 1:*

$$E\hat{g}(x) = g(x) \quad (10)$$

Kleywegt et al. [55] prove that the solution for SAA converges to solution of true problem with probability one. This proof is presented in form of the proposition 1 but let define some concepts before. First, we refer to the optimization problems corresponding to the true objective function  $g(x)$ , and sample average objective function  $\hat{g}_N(x)$ , as true and SAA problems respectively. Then let define  $s^*$  and  $\hat{s}^*$  to be the optimal values for true and SAA problems. In other words:  $s^* := \min_x g(x)$  and  $\hat{s}^* := \min_x \hat{g}_N(x)$ . Let also define the set of  $\mathcal{E}$ -optimal solutions as all the feasible solutions  $\bar{x} \in S$  where

$g(\bar{x}) \geq s^* - \varepsilon$  of a true maximization problem. Similarly, we denote the set of  $\mathcal{E}$ -optimal solutions for true and SAA as  $S^\varepsilon, \hat{S}_N^\varepsilon$  respectively.

**Proposition 1.** (i)  $\hat{s}_N \rightarrow s^*$  w.p.1 as  $N \rightarrow \infty$  (ii)  $\forall \varepsilon \geq 0$  the event  $\{\hat{S}_N^\varepsilon \subset S^\varepsilon\}$  happens w.p.1 for  $N$  large enough.

**Proof.** (i) Law of big numbers exerts that for any  $x \in S$ ,  $\hat{g}_N(x)$  converges to  $g(x)$  w.p.1. as  $N \rightarrow \infty$ . In addition, since the set of feasible solutions  $S$  is finite zero measure their union is finite also a zero measure that indicates the convergence of  $\hat{g}_N(x)$  toward  $g(x)$  uniformly in  $x \in S$ . In mathematic forms:

$$\delta_N = \max_{x \in S} |\hat{g}_N(x) - g(x)| \rightarrow 0, \text{ w.p.1 as } N \rightarrow \infty \text{ that follows } \hat{s}_N \rightarrow s^* \text{ as } N \rightarrow \infty \text{ since } |\hat{s}_N - s^*| \leq \delta_N [55]. +$$

(ii) Let define  $\rho(\varepsilon) = \min_{x \in S \setminus S^\varepsilon} g(x) - s^* - \varepsilon$ . Since for all  $x \in S \setminus S^\varepsilon$  it holds that  $g(x) > s^* + \varepsilon$  and the set  $S$  is finite then  $\rho(\varepsilon) > 0$ . Let choose a big enough  $N$  such that  $\delta_N < \rho(\varepsilon) / 2$ . Accordingly it holds  $\hat{s}_N < s^* + \rho(\varepsilon) / 2$  and for all  $x \in S \setminus S^\varepsilon$  it holds that  $\hat{g}_N(x) > s^* + \varepsilon + \rho(\varepsilon) / 2$ . It follows that  $\hat{g}_N(x) > \hat{s}_N + \varepsilon$  for all  $x \in S \setminus S^\varepsilon$  that means  $x$  does not belong to  $\hat{S}_N^\varepsilon$ . Therefore, we can inference that  $\hat{S}_N^\varepsilon \subset S^\varepsilon [55]. +$

The proposition 1 only describes the convergence of optimal value of the objective value and  $\mathcal{E}$ -optimal solution of SAA to the true problem by increasing the



number of random samples. After all, the main question that is sample size is still untouched. Next subsection discuss about the sample size and stopping criteria in SAA.

### 5.2.2 Sample Size and Stopping Criteria

From the previous section, we know that increasing the sample sized raises the SAA algorithm solution accuracy. However to apply the SAA algorithm there should be an exact sample size or a specific plan for increasing sample size until we reach to a stopping criteria. Kleywgt et al. [55] provided an upper bound for the sample size needed for SAA of a discrete optimization as follows:

$$N \geq \frac{3\sigma_{max}^2}{(\varepsilon - \delta)} \log\left(\frac{|S|}{\alpha}\right) \quad (11)$$

where,

$\sigma_{max}^2$ : is a form of variance of  $g(x), \forall x \in S \setminus S^\varepsilon$ ,

$\varepsilon$  and  $\delta$ : two positive numbers corresponding to  $\mathcal{E}$ -optimal solution and  $\mathcal{D}$ -optimal solution of true and SAA problems respectively,

$|S|$ : cardinality of feasible solution,

$1-\alpha$ : the probability of finding  $\mathcal{E}$ -optimal solution.

The upper bound in Equation (11) however, may be very too conservative and far from the real sample size. Moreover, calculating this bound is not an easy task since in many cases calculating  $\sigma_{max}^2$  and  $|S|$  gets very complicated. On the other hand, growth of the sample size adds up to the complexity and solution cost of SAA. Subsequently, in the literature of a SAA [55, 56] an algorithm is proposed based on tradeoff between the

optimal solution of SAA and the variation of optimality gap on one hand, and the sample size on the other hand. In continuous, a review is provided on the algorithm that is the adopted to solve the stochastic shoaling problem.

This algorithm is motivated based on calculating sample average function  $\hat{g}_N(\mathbf{x})$  for a feasible solution, instead of solving SAA problem that needs a heavy computation. Now instead of choosing a large  $N$  we can select a large  $M$  to accurately estimate the objective function  $g(\hat{\mathbf{x}}_N)$  by  $\hat{g}_N(\hat{\mathbf{x}}_N)$  where here  $\hat{\mathbf{x}}_N$  is the optimal solution of SAA. In other words, instead of solving SAA for a big number of  $N$  samples, we can replicate solving  $M$  numbers of SAA with sample size of  $N$  that might need much less computational effort, depending on the size of  $M$  and  $N$ . If the estimate of true objective function  $g(\hat{\mathbf{x}}_N^m)$  based on any  $m \in \{1, \dots, M\}$  optimal solutions ( $\hat{\mathbf{x}}_N^m$ ) from SAA is close enough to true optimal value,  $s^*$ , we have obtained the desired solution otherwise we need to increase the number of  $N$  or  $M$  or both and repeat the procedure.

By introducing the replication process, now we have  $M$  *i.i.d.* random variables  $g(\hat{\mathbf{x}}_N^m)$  according to  $M$  replication of SAA on samples with size  $N$ . Assuming that the distribution of  $g(\hat{\mathbf{x}}_N^m)$  is continuous, the probability that the solution of replication  $M+1$  achieves a better solution than previous  $M$  solutions is  $\frac{1}{1+M}$ . However, since our problem is an integer with discrete distribution, the probability of getting a better solution in replication  $M+1$  is less than or equal  $\frac{1}{1+M}$ . Subsequently, the larger  $M$  increases the probability of reaching to optimal solution.

However, to let the algorithm detect the  $\mathcal{E}$  -optimal solution, we need to know when we have obtained a good enough solution for one of the  $M$  number of SAA problems. In other words, we can stop when the achieved optimality gap for a given solution  $g(\hat{x}) - s^*$  is a short enough. However, none of the two components in calculating the gap is easily obtainable and we need to estimate them. Equation 12 represents the estimators for  $g(\hat{x})$ :

$$\hat{g}_{N'}(\hat{x}) = f_1(x) + \frac{1}{N'} f_2(\hat{x}, \xi^j) \quad (12)$$

Equation 12 provides an unbiased estimator for  $g(\hat{x})$ . Here  $N'$  is the size of new set of random samples  $\xi^j$  independent from  $M$  samples of size  $N$  that were used to simulate SAA.  $\hat{x}$  is an optimal solution from SAA that needs to be evaluated and we may refer to it as evaluation sample. Indeed, we are using  $N$  sets of random samples to evaluate the solution from SAA. The estimator for  $s^*$  is displayed in Equation 13.

$$\bar{s}_N^M = \frac{1}{M} \sum_{m=1}^M \hat{s}_N^m \quad (13)$$

where,  $\hat{s}_N^m$  indicates the optimal objective value for solving SAA problem number  $m$ .

Now we can use  $\hat{g}_{N'}(\hat{x}) - \bar{s}_N^M$  as the estimator of the optimal gap. Then assuming the independence between  $M$  samples of  $N$  size and  $N'$  evaluation samples, the estimator for variance of the gap, that could be a measure of solution quality, could be calculated as follows:

$$Var(\text{gap}) = \frac{S_{N'}^2}{N'} + \frac{S_M^2}{M} \quad (14)$$

where, the  $\frac{S_{N'}^2}{N'}$  is the sample variance of Equation 12 and  $\frac{S_M^2}{M}$  is the variance of  $\bar{s}_N^M$

that could be calculated as follows:

$$\frac{S_M^2}{M} = \frac{1}{M(M-1)} \sum_{m=1}^M (\hat{s}_N^m - \bar{s}_N^M)^2 \quad (15)$$

Obtaining the variance of the gap helps us to evaluate the acquired solution and provides a metric for stopping criteria.

### 5.2.3 SAA Algorithm

By defining all the necessary components for implementing the SAA algorithm the steps of this algorithm are portrayed as follows[55]:

- *Step 1-* Select the initial sample sizes  $N, M, N'$  and an increasing rule for each. One should choose  $M$  to obtain a sufficiently small  $\frac{1}{1+M}$  since it is the probability of obtaining better solution in replication  $M+1$ .
- *Step 2-* Generate a random sample of size  $N$  and solve the SAA problem for all  $m = 1, \dots, M$ . We refer the optimal value by  $\hat{s}_n^m$  and the optimal solution by  $\hat{x}_N^m$ . For replications  $m = 1, \dots, M$  apply the following steps *i* to *ii*:
  - i) Calculate the optimality gap estimator  $g(\hat{x}_N^m) - s^*$  and its variance.
  - ii) If the optimality gap estimator and its variance are small enough then select the best solution and Stop.

- *Step 3*- If the optimality gap or variance are note in the appropriate bound then increase the either size of  $N, N'$  or both and return to Step 2.

#### 5.2.4 Results of SAA Application on Stochastic Shoaling Problem

After the introduction to the concept and procedure of SAA, in this section presents the result of SAA application on the stochastic shoaling problem PORD. To investigate the effect of different sample sizes, several tests with different setups of sample size have been implemented. In general, two scenarios were examined as follows:

- Scenario 1- PORD model was solved by approximating true objective function with sample average of different sizes. Indeed, we solved the SAA with the sample sizes that are displayed in Table 4. This scenario does not consider any evaluation set was since we wanted to investigate the convergence of the true objective function with increasing sample size.

**Table 4 The sample sizes for running the first scenario of SAA**

Sample Type	Sample Size
N	10,20,...,90,100
M	1
$N'$	0

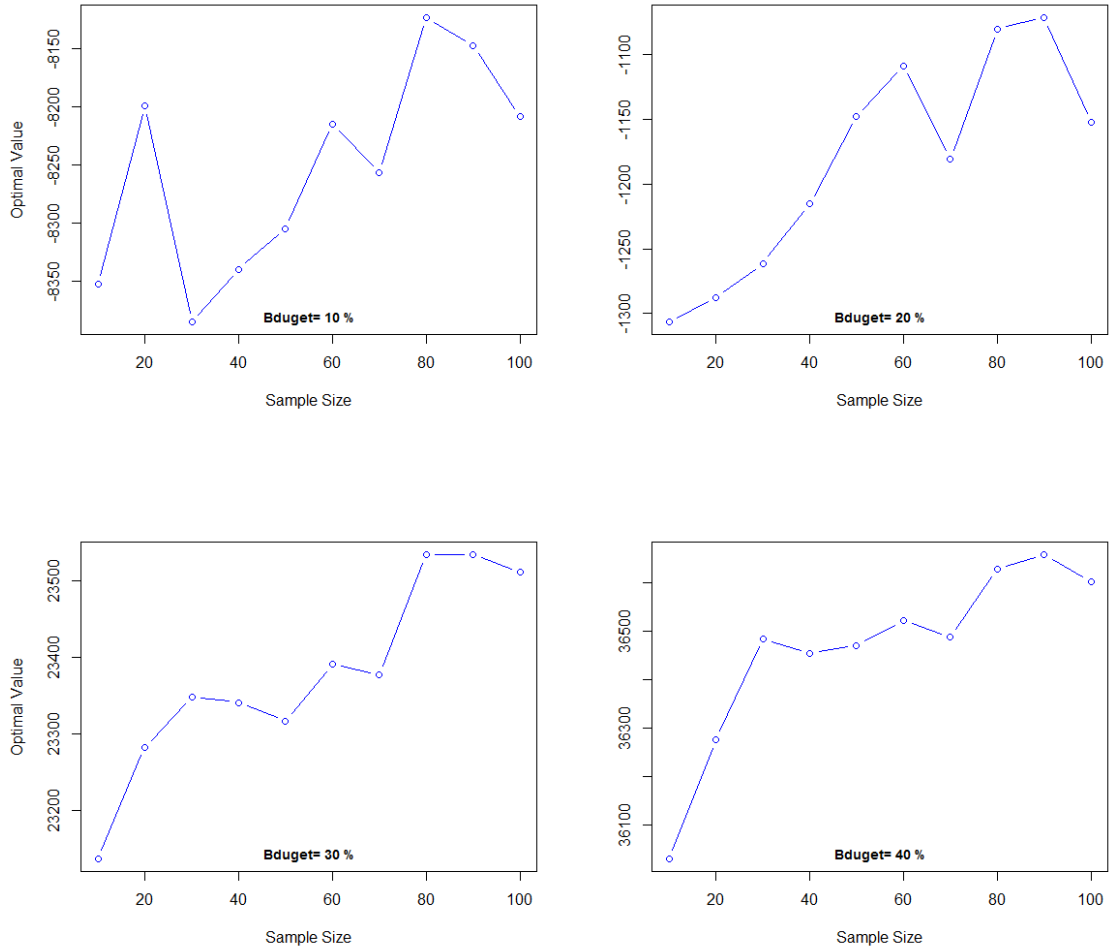
- Scenario 2- This scenario follows the algorithm provided in section 5.2.3 and considers an evaluation random set for examining the stopping criteria. The parameter setup for this scenario is presented in Table 5.

**Table 5 The sample sizes for running the second scenario of SAA**

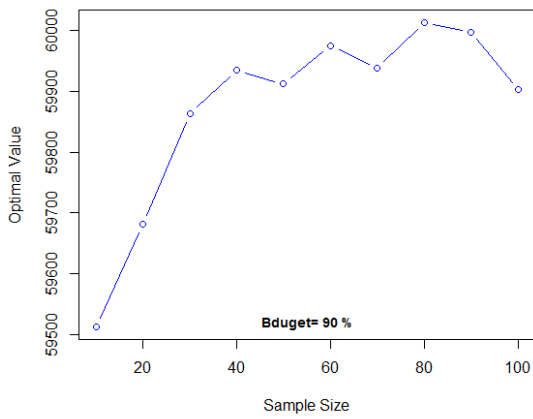
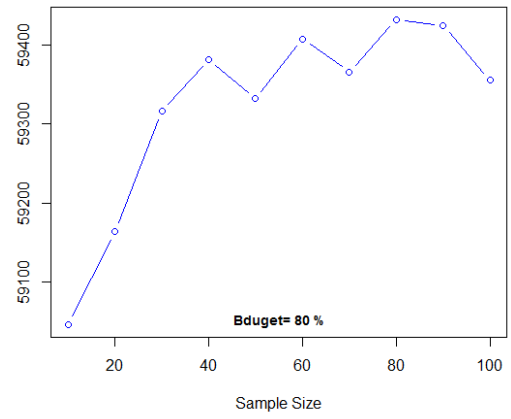
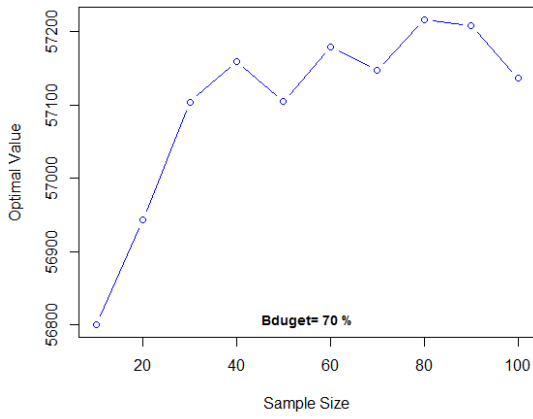
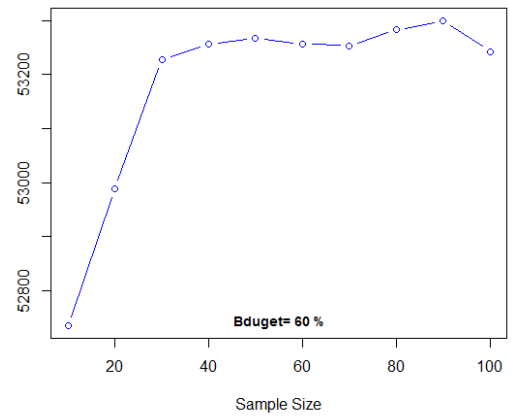
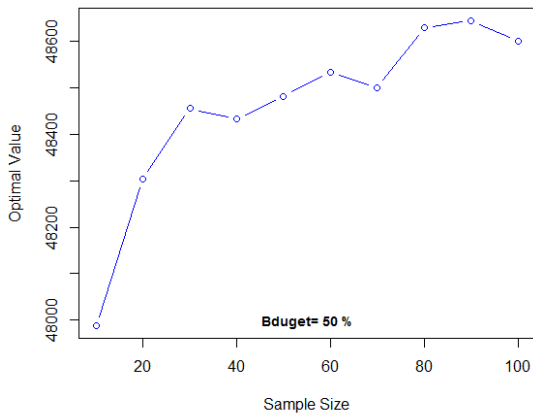
Sample Type	Sample Size
N	2
M	25
$N'$	100

For both scenarios nine budget conditions have been considered including tenth multipliers of the requested budget (10%, ... ,90%). The results of scenario 1 are presented in Figure 7. In this scenario we examined ten different approximations of objective functions (ten different sample sizes of 10, 20, ...,100 )using sample average to solve PORD problem. These approximate sample averages are exhibited in Equation (16):

$$g(x) = f_1(x) + \frac{1}{N} \sum_{i=1}^N f_2(x + \xi_i), \quad N = 10, 20, \dots, 100 \quad (16)$$



**Figure 7 Trend of optimal solution using sample average approximation for different sample sizes (M=1, N=10,....,100)**



**Figure 7 Continued**



As it is clear from this figure except the first budget condition (10%), the other results represent a convergence by increasing the sample size as it is expected. The result of first budget scenario even though that does not display a vivid convergence, does not have very large variation. The standard error of this result is 89.2 that is almost one percent of the best solution. Hence, we can expect by increasing the sample size beyond 100, we observe gradual convergence and smaller variation.

In scenario 2, we applied a SAA method where twenty-five replications of PORD problem with sample average approximation of size two were solved. It means that each optimization problem considers  $N=2$  number of random samples to approximate its objective function as it is illustrated in Equation (17):

$$g(x) = f_1(x) + \frac{1}{2} \sum_{i=1}^2 f_2(x + \xi_i) \quad (17)$$

This objective function is a smaller version of the functions that were used in scenario 1. After obtaining the optimal value for twenty-five replications, the average of all optimal solutions was taken as the estimator of problem optimal solution  $\hat{s}^*$  and their variance as the estimator of optimal solution variance  $\hat{S}_M^2$  as Equations (13) and (15).

Using twenty-five optimal solutions, we estimated  $\hat{g}_{N'}(x_N^m)$ , and their variance  $S_{N'}^2$ ,  $m = 1, \dots, 25$  as Equation (12) using  $N' = 100$  random samples. Thereafter, the optimality gap and its variance were estimated for each solution  $m = 1, \dots, 25$ . The estimated gaps, their standard deviation, their relative error compared to the estimated optimal solution  $\hat{s}^*$ , and the number of replication with the best gap is presented in Table 6.

**Table 6 The results of SAA algorithm including the best optimality gaps and their standard errors**

	Available Budget Condition								
	10%	20%	30%	40%	50%	60%	70%	80%	90%
Min Gap	319.5	559.0	47.2	216.9	14.8	391.9	6.6	8.7	29.3
Relative Err.	4.0%	94.6%	0.2%	0.6%	0.0%	0.7%	0.0%	0.0%	0.0%
Standard Error	223.2	234	247.6	285.4	293.6	280.2	268.4	267.9	272
Best Replication Id	25	19	5	19	13	22	4	6	10

Clearly from the results in Table 6, the obtained gaps and their standard errors demonstrate acceptable ranges considering their relative errors with estimated optimal solution  $\hat{s}^*$ . The only exception here is the solution for budget scenario 2 (20% budget available). Thus we could stop the algorithm here and there is no need for running another test with bigger sample sizes.

In parallel, we evaluated the results from scenario 2 with the results of scenario 1 for one-hundred sample approximation. This comparison provides more information about the quality of solutions in scenario 2. In addition to the comparison of the obtained objective values, we also compared the running times to investigate the computational efficiency of SAA in scenario 2. The results regarding this comparison are provided in Table 7. This table also shows the error of the solutions from other sample size approximation with one-hundred sample size and their corresponding computational time.

**Table 7 The comparison of errors and running times against scenario 1 with 100 sample average size approximation**

Applied Test		Available Budget Condition									Run Time (s)
		10%	20%	30%	40%	50%	60%	70%	80%	90%	
Scenario 1 - Sample Size	10	-1.75	-13.41	1.59	1.56	1.26	0.95	0.59	0.52	0.65	6.6
	20	0.12	-11.77	0.97	0.89	0.61	0.48	0.34	0.32	0.37	37.1
	30	-2.14	-9.51	0.69	0.32	0.30	0.03	0.06	0.07	0.07	42.4
	40	-1.59	-5.50	0.72	0.40	0.34	-0.03	-0.04	-0.04	-0.05	76.8
	50	-1.17	0.40	0.83	0.36	0.24	-0.05	0.06	0.04	-0.01	203
	60	-0.07	3.77	0.51	0.22	0.14	-0.03	-0.08	-0.09	-0.12	2919.
	70	-0.58	-2.49	0.57	0.31	0.20	-0.02	-0.02	-0.02	-0.06	222.1
	80	1.04	6.25	-0.10	-0.07	-0.06	-0.08	-0.14	-0.13	-0.18	538.4
	90	0.75	7.01	-0.10	-0.15	-0.09	-0.11	-0.13	-0.12	-0.16	487.0
Scenario 2		2.33	-0.18	-0.36	0.10	0.11	0.38	0.68	0.62	0.59	31.7

The result in table 7 illustrates a decreasing trend in error by enlarging the sample size. However, similar to the plots in figure.... this is not entirely true for the problem with twenty percent available budget. Other observation from this table is general increasing trend of the running time that could be expected. It should be noticed that in average half of the running time is the regarding to the twenty percent budget scenario. After all, it is observable that scenario 2 provides a descent error comparing to the results of scenario 1 and except the tests with 10, 20, 30 and 40 sample sizes offers significantly shorter run time with similar error rates. Therefore, the attained results illustrate the efficiency of applied SAA method with shorter sample sizes in approximate objective function ( $N$ ) and big number of replications instead of choosing big sample sizes for solving the approximate objective function.

### 5.3 Evaluation of Deterministic Solution with SAA

This section investigates the quality of solution achieved with the proxy deterministic method compared to the solution from SAA. To this end, after obtaining the optimal solution of the proxy deterministic problem (MPORD) that is represented by  $\hat{x}_d^*$ , using Equation (9) we obtained the estimation of objective function  $\hat{g}_{N'}(\hat{x}_d^*)$  and its variance for  $N' = 100$  random samples. Then we evaluated the solution quality by calculating two optimality relative errors, the first between the objective function estimation  $\hat{g}_{N'}(\hat{x}_d^*)$  and the optimal value of deterministic  $\hat{S}_d^*$ . The second the relative gap is between  $\hat{g}_{N'}(\hat{x}_d^*)$  and the optimal solution from the SAA scenario1 with one-hundred sample sizes  $\hat{S}_{SAA(100)}^*$ . Table 8 illustrates these relative gaps and the standard error of  $\hat{g}_{N'}(\hat{x}_d^*)$ .

**Table 8 Comparing the result of MPORD with SAA**

Metric	Budget Condition								
	10%	20%	30%	40%	50%	60%	70%	80%	90%
$\frac{\hat{g}_{N'}(\hat{x}_d^*) - \hat{S}_d^*}{\hat{S}_d^*}$	-12%	-20%	3%	-2%	-3%	-5%	-5%	-5%	-5%
$\frac{\hat{g}_{N'}(\hat{x}_d^*) - \hat{S}_{SAA(100)}^*}{\hat{S}_{SAA(100)}^*}$	2.4%	54.0%	-0.6%	0.0%	0.1%	-0.4%	0.6%	0.5%	0.6%
$Std[\hat{g}_{N'}(\hat{x}_d^*)]$	143.0	140.3	168.9	194.9	198.6	179.9	184.9	187.2	187.5

The result in table 8 reveals that the deterministic proxy of the stochastic shoaling (MPORD) provides a very descent solution competing with SAA results. This solution even gets more credit noticing its short running time of 0.8 minute. The quality of MPORD could be interpreted based on the very short support of random variables that includes only five situations (losing 0 to 4 foot of depth) and the specific structure of waterway networks.

At the end, it should be mentioned and acknowledged that the obtained results in this chapter are only based on one realization of shoaling probability. This realization might not be the true representation of the shoaling probability for all locks/dams, it is obtained from a simple analysis over some shoaling data sample. Besides, to make a solid conclusion, the analysis provided in this chapter should be tested for sensitivity against several probability distribution realizations. In other words, the obtained results of this chapter could not be generalized to make final decision and should accompanied with multiple other tests on different shoaling probability distributions.

In this chapter, we considered two different methods for taking account of stochasticity in dredging problem we referenced as stochastic shoaling. The first method is a proxy deterministic version of the problem that represented significant amount of saving for some budget scenarios. The second is a stochastic method based on Monte Carlo simulation and uses averages of sample random known as SAA. In fact, SAA approximates a two-stage problem where the decisions are made at first stage the consequents of those decisions reflect in second stage. The results of SAA showed that a stopping measure for our problem is achievable even with moderate sample sizes to

obtain qualitative enough results. Finally, the solution of deterministic proxy method was compared with SAA as a real stochastic solution. The finding discovered that due to the structure and limited probability support of our problem, the deterministic version could provide quite acceptable results with much shorter running time.

## CHAPTER VI

### MINIMIZATION COST MODEL ON A PROBABILISTIC MULTIMODAL NETWORK

In previous chapters the dredging problem was investigated comprehensively and several models were developed to assist finding the optimal allocation of dredging fund. However, in former models we only considered the water channels as the core elements for maintenance modeling and did not address other crucial elements of the waterway system that are locks/dams, or other connected land-side modes including highways and railways. While dredging maintenance budget allocation is the main purpose of this research, failing to address the mentioned elements does not lead to a system wise optimal solution and the achieved results from former models may land far from the expected optimal decisions in reality. Accordingly in this chapter we model the waterway maintenance and dredging budget allocation in context of a multi-modal network, taking account of locks/dams as the other major marine element as well as highways and railways as the landside mode connected to waterways.

In addition to the multi-modal consideration, this chapter provides a whole new perspective toward modeling dredging and locks/dams maintenance and budget allocation. So far, all the developed models were based on maximizing the marginal benefit of dredging, however in reality dredging or improving locks and dams does not add throughput to the waterway system and no marginal benefit is observed. Instead, waterway maintenance decreases the cost of marine transportation and improves the transportation fluidity. In consideration of this new horizon to the problem, the models

developed in this chapter aim to minimize the transportation cost on waterway system by optimal maintenance-budget allocation among elements of system through a multi-modal network.

Lastly, the maintenance problem is still modeled as stochastic problem and we need to adopt a method that could model the stochastic effects. The results of chapter 5 though revealed that the solution of proxy deterministic method provides a good enough solution for waterway system due to the specific structure of the network and very small support for the possible shoaling. Subsequently, the selected method for solving the problem of this chapter is still the proxy deterministic one due to its fast performance. In this chapter, we first provide an introduction to the costs of the waterway system. Then we provide the multi-modal model for solving the cost minimization problem and at the final part display the results of new model Ohio River with more than six-hundred mile length that is a very important marine corridor in the nation.

## **6.1 Waterway Costs and Dynamics**

Waterways have their own costs to operate marine transportation, to keep these costs as low as possible they require a continuous maintenance and rehabilitation. In fact, the cost of freight movement on a waterway depends on the total vessel-hour needed for freight movement. It means the fewer number of vessels traveling in the shorter time between a pair of origin-destination provides cheaper transportation and promotes higher rate of waterways use. However, two major problems exist in keeping the marine cost low; first is shoaling or losing the waterways depth, and the second is the unscheduled



delay that happens at locks/dams. The first problem decreases the effective depth of a channel (drafts) that does not allow use of heavier barges, thus for transporting a given amount of freight more barges and vessels are needed which causes additional cost. The second problem, i.e. unscheduled delay raises the vessel operation time and hence elevates the cost. Consequently, this chapter opens a new window toward the maintenance problem. The former models optimize the system through maximizing the system benefit (transported freight tonnage) by dredging that results in waterways capacity increase. However, there are many difficulties in defining the waterways' capacity and relating it to waterways' depth. In fact, in reality that kind of capacity does not exist and shoaling does not affect the amount of tonnage transported but the cost of transportation. Losing depth and happening delays on locks/dams only increases the mentioned costs or movement friction. In other words, these problems interrupt the fluidity of freight movement.

## **6.2 Methodology**

This chapter introduces a model that, unlike the former models, minimizes the cost of transportation across a multi-modal network by determining a set of optimal dredging and lock/dam maintenance operations. The dredging in this model has two main effects on the system: first it causes a local rise in the throughput by allowing heavier barge movement and thus higher tonnage be transported that results in heavier loading/unloading. Second it reduces the number of needed vessels to carry the same amount of freight allowing heavier barges. The first effect could impose heavier flow

to/from landside, and landside limited capacity should be considered. Whereas the second effect directly decreases the vessel cost.

In the case of locks/dams, delay reduction is considered as a random variable for a given scale of improvement. Hence, by improving locks/dams one could expect that delay expected value would reduce. Due to the exponential distribution of lock/dam delay, their expected value shapes up to a diminishing nonlinear function. To adopt this nonlinearity into the model, a piecewise linearization approach is used.

In addition, the model counts for connectivity to landside transportation by restraining the waterside improvement that causes temporal tonnage leap more than the available landside capacity. Hence, improving the water sided should consider the limited capacity on the landside, and if there is not enough capacity for the temporal leap due to the higher drafts, spending resources on dredging more is fruitless.

The other issue that the model should take care of is the stochastic shoaling of the waterways. To consider this probabilistic behavior the deterministic proxy method, as was explained in chapter 5, is adopted. Similar to chapter 5, this problem is modeled as a two-stage decision-making problem where the dredging depth should be selected such that the expected value of total cost at the end of second stage is minimized. Thus, the depth in the stage after dredging stage is known and optimal decisions are made regarding this knowledge.

### *6.2.1 Problem Statement*

Having a multimodal network including waterways, and locks/dams on waterside and

highways and railways on landside, we have a multi-modal problem. The problem is to determine the maintenance decisions or allocated funding for dredging and locks/dams maintenance that minimize the total cost of waterside transportation called as the optimal maintenance decisions. Every waterway network suffers from two main deteriorating processes: first losing depth of waterways due to shoaling, and second locks/dams operation failure. These decays cause a general system interruption that cause longer travel time and higher number of needed vessels to carry the freight. Accordingly, to keep up the efficiency and accessibility level of a waterway system there is a need for continuous maintenance and rehabilitation of waterway elements, however, due to the limitation of available budget it is desired to find the optimal maintenance decision with available budget. This said, one should be aware of the connection between the waterways and landside transportation facilities. Any decision about improving waterside transportation should be taken in a multimodal context, since some portion of carried freight through the waterside originates from or sinks to some landside origin or destination and should take landside modes. Thereupon there should be enough capacity on these modes to allow instant increase in waterside throughput. This consideration could be taken care of with adding a new constraint to the problem. Thus, the problem is identifying the optimal maintenance decision with considering the multimodal connections.

### *6.2.2 Intermodal Model*

The model developed in this section is a mixed integer linear program that minimizes the

total cost of a waterway system by selecting the optimal maintenance decisions. This model is defined on a multi-modal network of waterside links and locks/dams that are connected to some landside ODs. Since this problem is a two-stage stochastic problem, a proxy deterministic method similar to chapter 5 is developed to model the stochastic shoaling.

The developed model minimizes an objective function that is the summation of all costs along each single route. The cost on each route is built based on the cost of vessel-hour on that route. The draft of route, which is lowest navigable depth of all segments along that route, and the amount of delay on locks/dams determines the overall cost of route. Therefore, the model tries to minimize the total cost through increasing depth of waterways and reducing the delay happening in locks/dams. The waterways' depth increase is a direct linear impact of a dredging operation, meaning that  $i$  foot of additional depth is achieved by  $i$  foot dredging. In reality locks/dams' reduced delay is a random variable, meaning that after any improvement there is still some chance for breaking out and delay has a probability distribution. Thus for each given amount of improvement there exists a probability distribution for the failure occurrence. Usually by increasing the improvement scale, the mean and variance of failure decrease. However determining the exact distribution, given a specific unit of improvement, needs some analysis on historical data. For this model, we use the reduced delay instead of delay itself to remove the need for additional information of the initial delay of locks/dams. To take account of delay stochastic behavior, the developed model uses the mean value of reduced delay for each given improvement. Subsequently if an improvement  $i$  is selected

for a given lock/dam, the effect of that improvement would be  $E(Dely_i)$ , which reads as the expected value of delay reduction if improvement  $i$  is applied on the lock/dam. Now the model needs a pattern to describe the relationship between the improvement and its corresponding mean of reduced delay. For the rest of this research, a power function is assumed for this relationship that has a diminishing behavior; means the slope of mean reduced delay gradually decreases by increasing the improvement unit.

Each landside OD is connected to at least one waterway segment through one or more routes/modes (highway, railway). All the landside modes have some available capacities to operate at the desirable level of service (D) that do not allow any additional traffic, caused by the instant additional tonnage due to waterside improvement, beyond their capacities. The developed model is presented as follows. First, the variables and parameters that are needed for the model are introduced, and the model is illustrated afterwards

- Variables:

$d_i^k$ : the binary decision variable on segment  $i$ , that is 1 if segment  $i$  is dredged for  $k$  foot of dredging and 0 otherwise,

$x_{i,1}^k$ : the binary decision variable on route  $i$  at stage one, it is 1 if all the segments along the route  $i$  are dredged for  $k$  ft or higher depth and 0 otherwise,

$x_{i,2}^k$ : the binary decision variable on route  $i$  at stage two, it is 1 if all the segments along the route  $i$  are dredged for  $k$  ft or higher depth and 0 otherwise,

$l_i$ : the improvement unit on lock  $i$  that results in the reduction of mean reduced delay of the lock,

$y_i$ : the mean reduced delay on lock  $i$  due to some improvement operation on the lock,

$C_{max,1}^i$ : the maximum cost on route  $i$  at stage one that is a combination of cost related to total number of trips and total delay cost,

$C_{max,2}^i$ : the maximum cost on route  $i$  at stage two that is a combination of cost related to total number of trips and total delay cost.

- Parameters:

$a_p$ : the capacity on landside route  $p$  that is connecting a dockage to a landside OD,

$b_i^k$ : the incremental increase in tonnage that is added to draft  $k$  of segment  $i$  due to 1 foot dredging,

$B$ : the available budget,

$Cd_i$ : cost of one foot dredging on segment  $i$  of waterway,

$Cl_i$ : the cost of a unit of maintenance on lock  $i$ ,

$Ct_i$ : the average cost of trip per mile due on rout  $i$ ,

$L(m)$ : the set of all landside routes that are connected to land origin or destination  $i$ ,

$M$ : a big number that is used as the penalty value,

$N_i^k$  : the number of trips that should be done on route  $i$  with draft  $k$  to meet all the demand,

$P_i^m$  : the proportion of land origin or destination  $m$  that travels on route  $i$ ,

$R$ : the set of all waterway routes,

$R(i)$ : the set of all water routes that are connected to land origin or destination  $i$ ,

$S$ : the set of all segments,

$S(i)$ : the set of all segments that are lying on route  $i$ ,

$UD$  : an upper bound on delays of all locks,

$V$ : the value or cost of one hour delay,

$$\text{Min} \sum_i C_{max,1}^i + C_{max,2}^i \quad (18-0)$$

$$\sum_i d_i^k C d_i^k + \sum_i l_i C l_i \leq B \quad (18-1)$$

$$\sum_k d_i^k \leq 1, \quad \forall i \in S \quad (18-2)$$

$$\sum_k k x_{i,1}^k \leq \sum_k k d_j^k, \quad \forall i \in R, j \in S(i) \quad (18-3)$$

$$\sum_k k x_{i,2}^k \leq \sum_k E(k) d_j^k, \quad \forall i \in R, j \in S(i) \quad (18-4)$$

$$\sum_k x_{i,1}^k \leq 1, \quad \forall i \in R \quad (18-5)$$

$$\sum_k x_{i,2}^k \leq 1, \quad \forall i \in R \quad (18-6)$$

$$\sum_{i \in R(m)} \sum_k x_i^k b_i^k P_i^m \leq \sum_{p \in L(m)} a_p, \quad \forall m \in OD \quad (18-7)$$

$$x_{i,1}^k N_i^k C t_i + \sum_{j \in S(i)} (UD - y_i) N_i^k V + (x_{i,1}^k - 1) M \leq C_{\max,1}^i, \quad \forall i \in R, k \in D \quad (18-8)$$

$$x_{i,2}^k N_i^k C t_i + \sum_{j \in S(i)} (UD - y_i) N_i^k V + (x_{i,2}^k - 1) M \leq C_{\max,2}^i, \quad \forall i \in R, k \in D \quad (18-9)$$

$$x_i^k, d_i^k : \text{binary} \quad \forall i \in R, k \in D \quad (18-10)$$

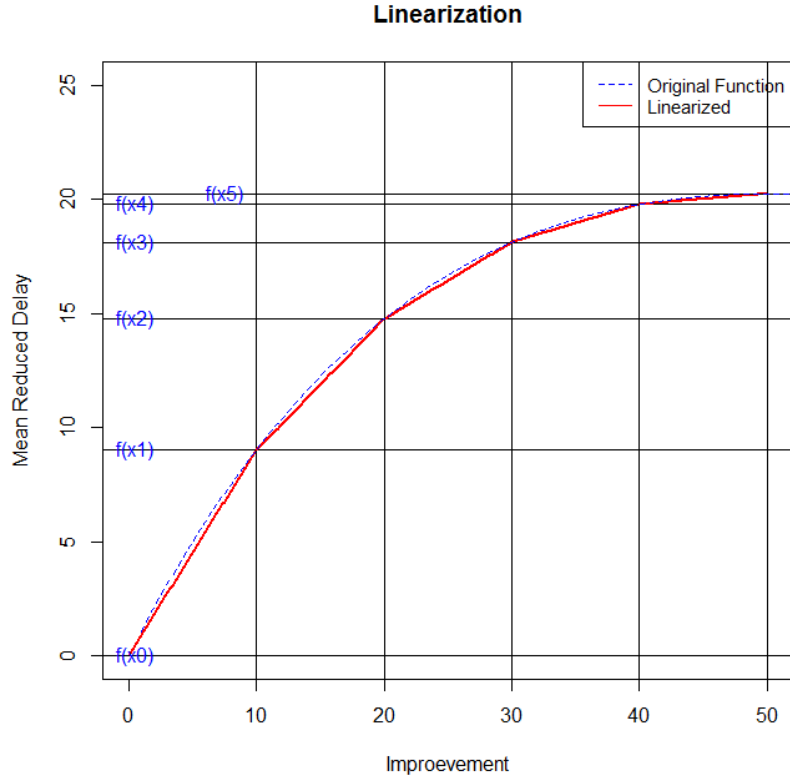
$$l_i, C_{\max,1}^i, C_{\max,2}^i \geq 0, \quad \forall i \in R \quad (18-11)$$

The objective function of this model minimizes the total cost in both stage one and two due to waterway interruption. This cost is a combination of the average cost of all voyages along each path plus the average cost of delay on all locks along that path. The constraint 1 indicates that the total cost for dredging and locks/dams improvement should be less than or equal to available budget. Constraint 2 indicates that each segment can have only one depth of dredging. Constraint 3 explains that if a route in stage one benefits from reduction in number of vessels by increasing the draft of route  $i$ , all of its segments should be at least as deep as  $i$  ft draft. Constraint 4 expresses that the depth of each route at second stage should be less than or equal to the smallest expected depth of its segments at stage two. Constraint 5 and 6 indicate that each route can have only one depth at first and second stages. Constraint 7 indicates the total flow that comes from or goes to a land point that travels through waterways should be less than total capacity of all possible land side routes to that point. It means the total tonnage that needs to travel in the land modes should be less than all land routes capacity. Constraint 8 and 9 identify



the depth of each route at stages one and two in order to minimize the total cost. There is a penalty term in this model that guarantees the maximum route cost is equal to cost of the route with selected depth. The route cost is the overall cost due to total number of vessels using route with selected depth and delay on all the locks/dams along that route.

The developed model is a MILP that could be a combination of linear and integer functions and variables. However the assumed the function of mean reduced delay ( $Y_i$ ) is a nonlinear function that could not be directly used in the developed model. In addition, the maintenance cost generally has a nonlinear function and in the numerical section, we have tested the effect of nonlinear cost function on fund allocation result. Consequently, to use these nonlinear functions a linearization method should be employed. To this end a piecewise linearization method is applied to provide a linear approximation of the power function. Figure 8 displays the power function and the approximated linear pieces. The original function is represented by dotted blue line and the piece linear sections are indicated with red lines.



**Figure 8 Process of mean reduced delay linearization**

In the linearization method, the function domain is divided into several sections, in this problem to 5 sections. Then the value of function is determined at the borders as we call them  $f(x_i)$ , afterwards the following constraints should be considered in the original MILP model:

$$y_i = \sum_j w_{ij} f(a_i), \quad \forall i \in locks \quad (18-12)$$

$$l_i = \sum_j w_{ij} x_j, \quad \forall i \in locks \quad (18-13)$$

$$\sum_j w_{ij} = 1, \quad \forall i \in \text{locks} \quad (18-14)$$

where,

$y_i$ : is the linear approximation of mean reduced delay on lock  $i$ ,

$l_i$ : the amount of improvement identified by the original model,

$w_{ij}$ : is the weight coefficient for linearizing the mean reduced delay of lock  $i$ ,

$a_j$ : is discretized domain values at start of each linearized piece ( $j = 0, 10, 20, \dots, 50$ )

where 50 is the theoretical maximum improvement scale,

Now adding constraints (12)-(14) the model is a complete MILP and could be solved with the classical optimization methods using the available software packages for optimization.

### 6.3 Numerical Results

The developed multi-modal model in this chapter is applied on the Ohio River, which is one of the most crucial portions of US national waterway system. In the remainder of this section, first a brief introduction is presented on the Ohio River characteristics and the problem input. Next, the result of numerical tests of the model is provided.

#### 6.3.1 Ohio River at a Glance

The Ohio River connects the six states of Illinois, Indiana, Kentucky, Ohio, Pennsylvania, and West Virginia as is displayed in Figure 9.



**Figure 9 A sketch of Ohio River position**

The Ohio River Basin (ORB) system includes about 2,800 miles of navigable waterway. The 65% of the 275 million tons transported as of 1999, are shipped inside the basin itself, through the 60 lock/dam facilities maintained by the USACE. Coal is the major commodity shipped through and within the Ohio River Basin, according to the large amount of reserves in the region. The other significant cargos include aggregates, petroleum, grains and chemicals shipped on the Ohio River Basin System [57].

The developed model in this chapter is only applied on the main stem of the Ohio River that consists of 21 lock/dams and approximately 700 miles length. A sketch of the main stem of Ohio River is presented in Figure 10.

# OHIO RIVER MAINSTEM NAVIGATION SYSTEM

## General Plan and Profile

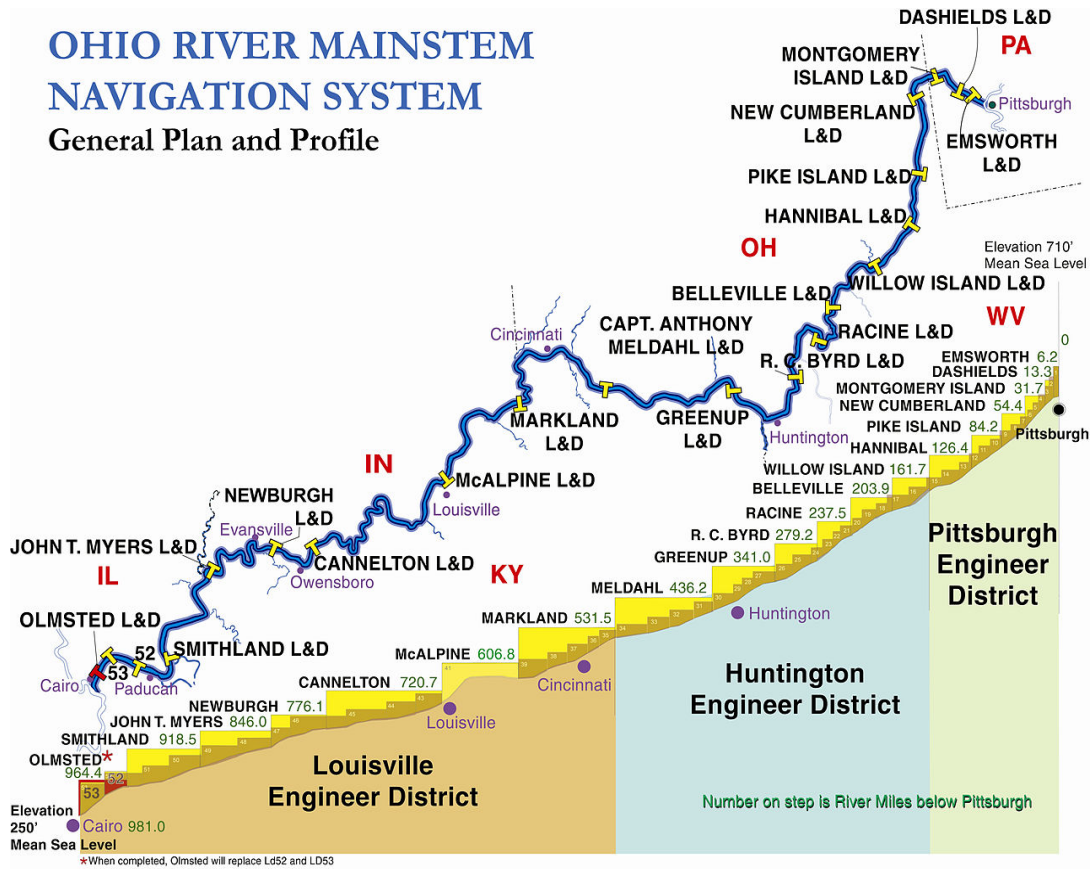


Figure 10 Ohio River main stem and its locks/dams [58]

The main stem of Ohio River is then divided into 51 segments that are connecting 21 lock/dams. All of 21 locks except three locks of Emsworth, Dashields, and Montgomery have 1200 foot lock chambers. The other three have 600 foot lock chambers.

To apply the model on this network we needed to prepare the model's input data. The input includes a large amount of information such as the number of vessels shipping on each route, the effect of draft on their number, the cost of dredging and lock/dam

improvement, the effect of one unit of lock/dam improvement on the reducing delay, the portion of demand that takes the landside modes and their capacity, etc. Accordingly, an exhaustive data preparation was needed before we started solving the model.

The information about the number of the shipping vessels on each specific draft of a route was extracted from the historical data. Using the average ratio of tonnage per barge for each draft and the tonnage demand for each specific draft, we then concluded the change of vessels number by change of draft. To assess the delay of the lock/dams, however, we did more calculation. Using a large database for each of the lock/dams, we needed to first detect when the delay has happened and afterwards, calculate the corresponding delay due to unexpected interruption. Writing a python code and developing a method to distinguish between the delay due to traffic queue and unwanted interruption, we extracted the distribution and average of delay. Then we assumed a power function between the amount of improvement and the reduced delay as displayed in Figure 8.

The other important information was the amount of cargo that took landside modes besides the landside routes that connect the marine network to landside origin-destinations. To prepare this data, we first identified all the major landside origin-destinations and the major highways or railways that connect them to Ohio River. Then we considered portions of tonnage from each waterway ODs that travels to land ODs. In estimating the available capacity, we explored whether the available capacity of landside modes is usually enough for moving cargo from the waterway. However, to test the effect of lack of capacity of landside modes, we tested some hypothetical scenarios.

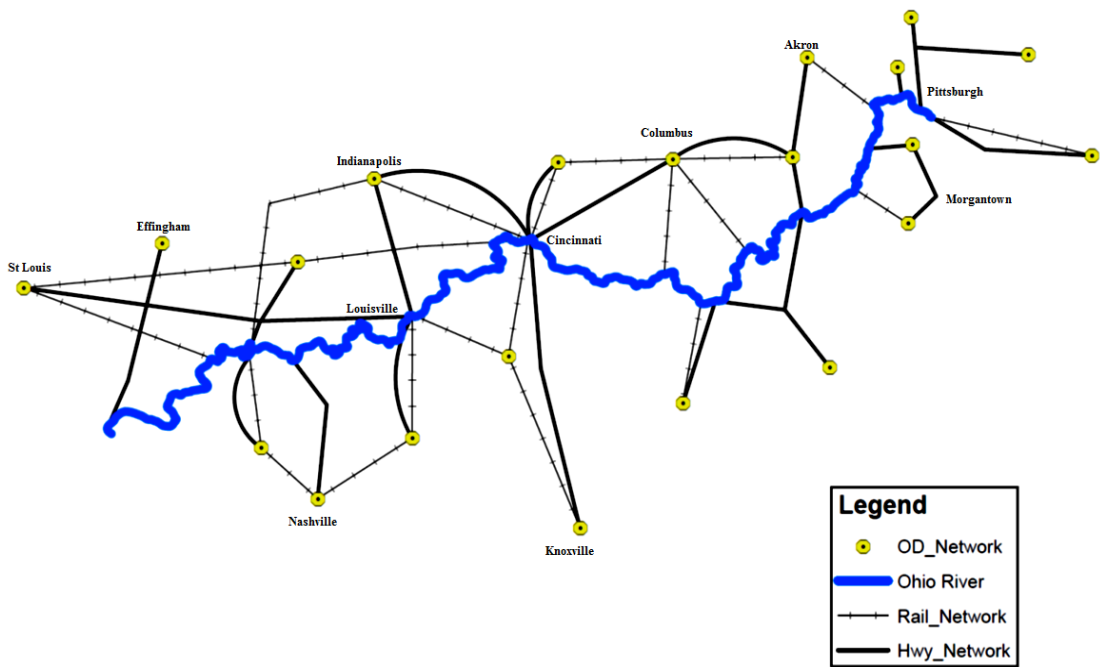
Finally, we needed to have some estimation on the cost of dredging and lock/dam improvement. In case of dredging, we used the information from the example in Chapter 5. While for the cost of lock/dam improvement we tested two cases. In the first case, a linear function with fixed rate as  $C_l = 12000l$  was investigated. In the second case, though, a non-linear function with an initial fixed cost was considered as:

$$C_l = 0.622l^2 + 12.6l + 1216$$

As it is clear, the second function causes higher cost for the lock/dam maintenance and it is expected that a higher portion of total budget is allocated to this maintenance compared to the first cost function.

### *6.3.2 Model Results*

The schematic network of the Ohio River as it is inputted to the model is presented in Figure 11. This Figure presents the river corridor and the connected railway and highway segments that connect the waterways to the landside ODs depicted with yellow circles.



**Figure 11 The Ohio River sketch in a multi-modal network**

After defining the components of the Ohio River for the model, including 51 waterway segments and 21 lock/dams, we tested the model for multiple input sets up. First, it was investigated that how the change of two crucial costs corresponding to vessel/mile and cost/hour delay could change the optimal results for the linear maintenance function. To this end, the model was tested for nine cross combinations of  $Ct = \{10, 25, 50\}$ ,  $V = \{350, 500\}$ , and  $Ct = \{50, 100, 150\}$ ,  $V = \{700\}$ . The results showed there is no important change due to different setups and hence it is not sensitive to these parameters with the range of variation that was tested. Thus the achieve results for all the of the different combinations is as presented in in Table 9 and Figures 12 and 13.

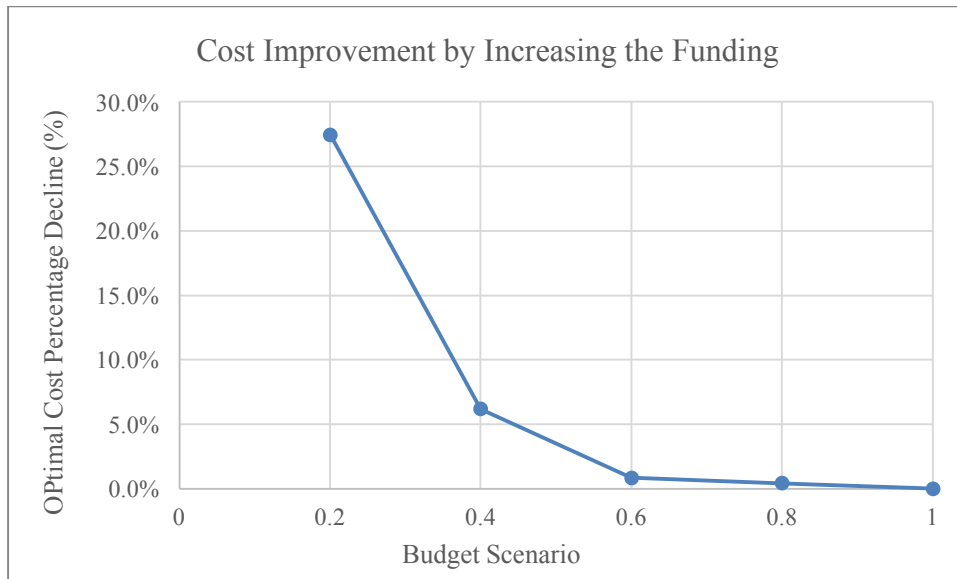


**Table 9 The optimal result of model for nine different combinations of vessel/mile and value/hour cost for linear locks' maintenance function**

Budget Scenario	OBJ Function (\$)	Improvement (%)	Available Budget (\$)	Lock Cost (\$)	Lock's Fund Allocated (%)	Optimal Gap (%)	Run Time (s)
0.2	94,706,653	27.5%	473,813	7,862	1.7	0.5	3691
0.4	78,905,067	6.2%	947,626	453,154	47.8	0.5	5406
0.6	74,927,125	0.8%	1,421,439	897,552	63.1	0.5	46
0.8	74,625,598	0.4%	1,895,252	1,260,000	66.5	0.4	6
1	74,307,763	0.0%	2,369,065	1,260,000	53.2	0	90

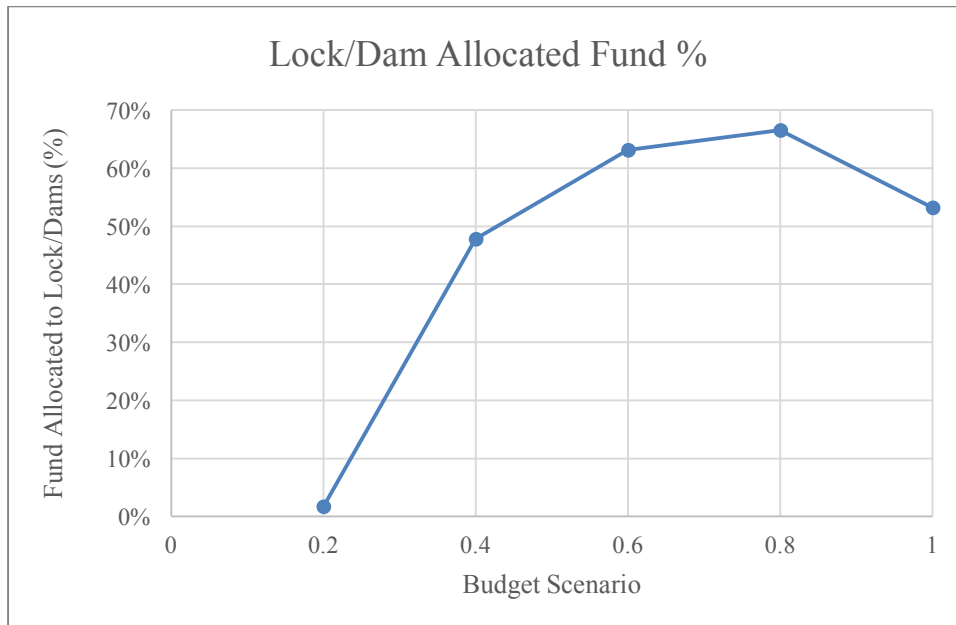
The result of the Table 9 illustrates that by increasing the available budget, the portion of budget allocated to lock/dam maintenance increases until it reaches its entire requested funding. The improvement column represents the percentage of difference of total cost for each budget scenario compared to the budget scenario of full budget.

Figure 12 and represents these percentage of difference.



**Figure 12 The percentage of difference between cost for different budget scenarios versus full fund scenario**

Figure 12 describes that even if only 20 percentage of the total requested budget is available, the optimal total cost is 27.5% higher than the cost when the full fund is available, and this difference is exponentially decreasing by increasing the available budget. Figure 13 illustrates the portion of allocated budget to lock/dam maintenance.

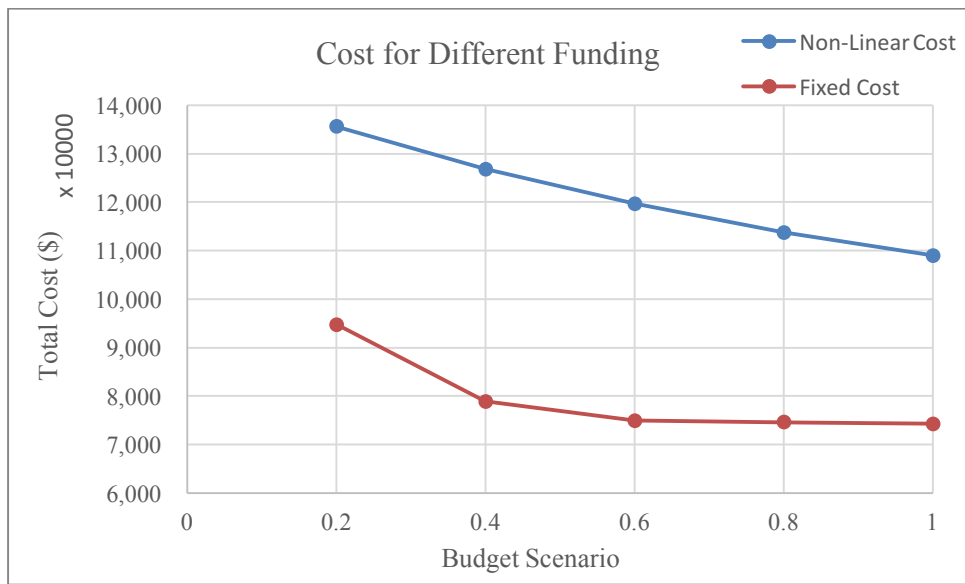


**Figure 13 The percentage of budget allocated to lock/dam maintenance**

Figure 13 shows a non-linear trend of budget allocation to lock/dam maintenance. The plot starts with a steep increasing slope and gradually loses its gradient by increasing budget until it receives its one-hundred percent requested budget. This trend illustrates that when the budget is low and there is not much flow on the river the priority is to fund dredging, but small increase in the funding changes the allocation balance in favor of lock/dam maintenance. One other test was conducted for the case that we have a non-linear increasing cost for lock/dam maintenance. The result of this test is presented in Table 10, and Figure 14.

**Table 10 The result of application of model whit a non-linear locks' maintenance function**

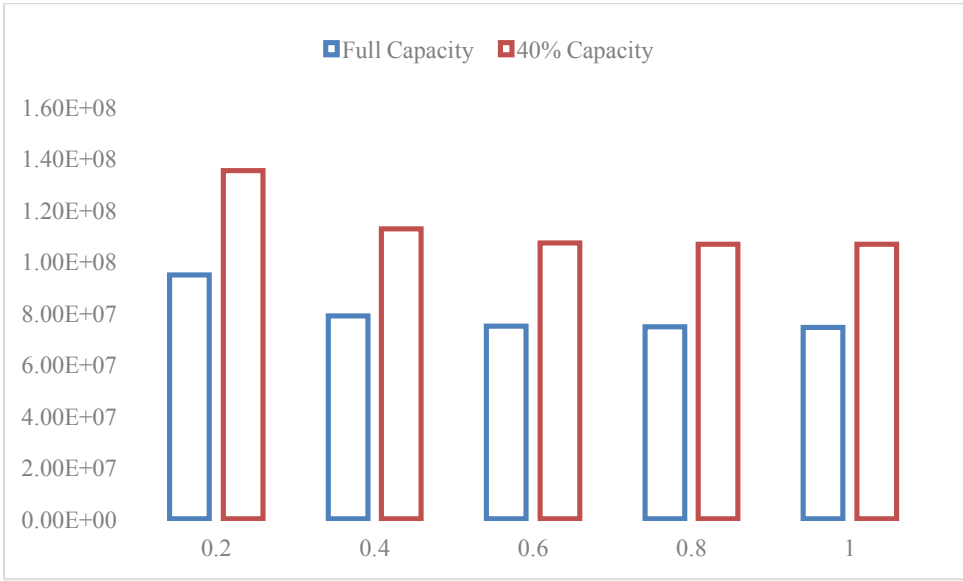
Budget Scenario	OBJ Function (\$)	Improvement (%)	Available Budget (\$)	Lock Cost (\$)	Lock's Fund Allocated (%)	Optimal Gap (%)	Run Time (s)
0.2	135,603,533	24.4%	473,813	0	0%	1	5404
0.4	126,828,910	16.3%	947,626	392,838	42%	1.2	5409
0.6	119,684,094	9.8%	1,421,439	894,076	63%	0.6	5401
0.8	113,768,892	4.4%	1,895,252	1,366,405	72%	0.5	370
1	109,015,375	0.0%	2,369,065	1,845,179	78%	0.5	125



**Figure 14 Minimized cost for linear and non-linear locks' maintenance cost function**

The result of Table 10, and Figure 14 indicates that by increasing of lock/dam maintenance cost the cost of the system increases significantly and dredging operation could not merely compensate the system costs.

In summary, the model was tested on the real network of the Ohio River and showed capability of finding optimal solutions. While for the models provided in chapter 3 and 4 some easy guess and simplifying heuristics were available, it is much more difficult to find a near optimal solution for the multi-modal problem with the definition introduced in this chapter 5. In addition, we also tested the effect of changing the landside modes' capacity on the cost and the optimal solutions. The landside modes' capacity was reduced to forty percent of the full capacity needed to accommodate the additional tonnage when 100 percentage budget is available. The results display a clear rise of the total system cost, about 42%, due to lack of capacity on landside modes.



**Figure 15** The comparison of optimal solution between full landside capacity and 40% available capacity

Accordingly, using the multi-modal model proposed in this chapter significantly assists to obtain exact optimal solution for the problem considering all of the system components.

## CHAPTER VII

### CONCLUSION

The U.S. waterway system carries billion dollars value commodity across the nation each year. It supports the more than 75 percent of the import and export cargos and this percentage is expected to increase. A routine problem, however, with the waterway system is that it is prone to losing depth and effective shipping draft due to the settlement of sediments from tidal flows. Similarly, locks/dams could experience deterioration and cause long delays for the traveling vessels through unexpected failures that happen, as they age and decay over the time. Consequently, this system demands maintenance and rehabilitation on both waterway segments and locks/dams. The waterway segments are maintained by removing the settled sediments from the channel bed; this operation is called dredging. Likewise, locks/dams need some routine maintenance to reduce the probability of unscheduled interruption. Both of these two maintenance operations are too costly while the available budget is not usually enough to meet the entire requested maintenance budget. Moreover, even if the budget is enough, it is not an easy task to determine how to optimally allocate the available budget to different maintenance operations. Facing a decreasing operations and maintenance fund, the U.S. ACE has to make a balance between the requested maintenance projects and the limited available funding. This research has a goal of developing scientific tools and models to facilitate the maintenance decision dealing with budget constraints, system randomness and network system effect so that fund spent would have a maximum system effect in terms of system capacity.

This study specifically focuses on optimizing the selection of maintenance projects so that budget may be used to fund projects with the maximum system benefits. Selection from a given set of requested projects to fund naturally lends itself to the class of the famous knapsack problem, clearly an NP-Hard problem. However, our study problem comes with an additional complexity: our problem has a network effect. The network effect implies that decision for a project often is dependent on other projects. A simple explanation to it is that an enlarged shipping capacity between two ports requires both ports to have a deeper draft. As a result, the conventional methods developed to solve the knapsack problem are not applicable to this problem. To this end, for the first time we developed some analytical exact and heuristic methods to solve the waterway maintaining problem considering different conditions. First, a model was proposed to identify the optimal selection of water segments to be dredged based on a zero-one integer-programming model that was referred to as ORD. This model assumes the incremental tonnage surge, due to increasing the draft of a path, is marginal benefit of dredging over a path and correspondingly determines the optimal dredging actions that maximize the total benefit of the system. The model then was tested on some real examples of US maritime network and its results were confirmed by comparing to the historical maintenance decisions in reality. In the next step, the ORD model was extended to be able of considering partial funding, meaning that the optimal solution now determines extent of maintenance for each water segment dredging. Hence, zero means that the segment is not selected for dredging and any integer number other than



zero indicates the depth of dredging on the corresponding segment. This model was called continuous dredging and was tested on two big networks.

The models developed so far all consider a deterministic condition for the waterway system. However, in reality the shoaling phenomenon is a random process that is also a function of dredging depth each time. Deeper draft has faster shoaling. In other words, spending more funding and dredging for deeper drafts does not necessarily lead to an expected higher draft at the end of programming period. In light of this fact, in the fifth chapter the dredging problem was modeled as a two-stage model where the decisions made at first stage are followed by stochastic consequences in the second stage. Therefore, to make an optimal decision on the system, we needed to solve a stochastic two-stage problem. To solve this stochastic problem, two different methods were developed: a proxy deterministic method, and a Monte-Carlo based simulation method that uses averaging over random samples referred to as Sample Average Approximation (SAA). The results of first method revealed that considering the stochastic shoaling effect could improve the objective functions up to twenty-four percent depending on the available budget. The second method was also successfully tested on the Great Lake example and the result showed that due to the specific structure of the network even moderate sample size could meet the stopping criteria and achieve acceptable results. The second model is a the correct method for solving a stochastic two-stage problem and the comparison of two methods displayed that the proxy deterministic provides quality solutions comparing to SAA while offering shorter

running time. The reason for this observation could be addressed to the special structure of the waterway network and the small support for the probability of shoaling.

In the last chapter, we position the waterway system maintenance in context of a multi-modal model by including all the elements of the waterway system and the connected landside transportation. The developed model determines the optimal maintenance action for both dredging and locks/dams maintenance while considering the availability of capacity on the land-side. The problem is defined as a stochastic problem considering the random shoaling and the proxy deterministic method is adopted to solve the model. Due to non-linearity in lock/dam's maintenance performance function with costs, a piecewise linearization is used to keep the model as MILP. The Ohio River, one of the largest integral sections of US waterway network, is used for numerical test. The result showed that the optimal solution is not dependent on the value of time and the cost of vessels travel on the network. However the limit of landside modes' capacity and also the change of the cost function of lock/dam maintenance would change the optimal solutions.

Due to time and funding of this study, many factors have not been considered such as the effect of cost fluctuation of the marine transportation on the amount of OD demand using this system. In this study, it was assumed that the demand is fixed and deterioration of the waterway system only increases the transportation cost. As another suggestion, one could alter the assumption of independency of random shoaling between different waterway segments. In chapter 5, to model the stochastic shoaling problem, it was assumed independent random shoaling between water segments, another strong

assumption that may defy reality to varying extent. We therefore recommend that future studies take care of all these effects and factors.

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