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Navigational channel dredging is vital to maintaining efficient inland and coastal waterborne freight. We develop and compare three optimization models that shift dredging project planning to a system-wide, performance-based frame-works. The baseline estimates route-based shipping costs under simplified assumptions; the second adds segment-level initial depths and their effects on route capacity; the third extends to two years with stochastic shoaling and adap-tive second-year reallocation under inflation-adjusted costs. A mixed-integer, two-stage structure links dredging to route draft, lock improvements to delay reduction, and route capacity to vessel costs and OD demand. In the Ohio River Basin of 428.7 miles and 27 reaches, the second model cuts dredging costs by up to 38.5% while maintaining the same level of optimality as the prior optimization model; the third further reduces system-wide shipping costs, remains robust in sensitivity tests, but is computationally intensive. New models are shown numerically to dramatically improve on the efficiency of fund allocation.</td></tr>
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Table of Contents

1 Project Description

1.1 Introduction

Navigational channel dredging is a fundamental component of the U.S. maritime transportation network, ensuring the efficient movement of goods and commodities through ports, harbors, and inland waterways. The U.S. Army Corps of Engineers (USACE), as the federal agency responsible for maintaining these channels, manages dredging project selection to remove sediment buildup that can impede vessel traffic, reduce channel depth, and restrict cargo capacity. Without regular dredging, critical shipping lanes would become unnavigable, directly disrupting domestic and international trade.

The economic importance of dredging is substantial. The U.S. maritime transportation system moves more than 2.3 billion tons of domestic and international cargo annually, including agricultural products, petroleum, coal, chemicals, and manufactured goods. The inland waterway system alone transports over 600 million tons of cargo per year, supporting industries that rely on bulk transport. Waterborne commerce is vital to the U.S. economy, contributing approximately 5.4 trillion USD in economic activity and supporting over 31 million jobs. The cost-effectiveness of maritime transportation further underscores its importance. Shipping by barge costs significantly less than rail or truck transport, with an estimated cost of 2 to 3 times lower than rail and 10 times lower than truck per ton-mile. This makes navigable waterways an indispensable component of the national freight system, particularly for moving heavy, low-value bulk commodities efficiently.

Despite its crucial role, dredging presents several challenges. Funding constraints require prioritization of dredging projects to ensure that limited resources yield maximum economic and operational benefits. System conditions, such as sediment disposal, water quality impacts, and ecosystem disruption, necessitate compliance with stringent regulations. Operational complexities arise from the need to coordinate dredging schedules, optimize equip-ment deployment, and maintain access for commercial and military vessels. The increasing size of modern vessels, including post-Panama ships, also demands deeper and wider channels, adding pressure to maintain and expand existing infrastructure.

Beyond these challenges, a fundamental problem remains: how to correctly and efficiently allocate limited maintenance funds for dredging and general maintenance projects across a network of interdependent waterway segments and locks. While dredging projects are often evaluated based on local cost-benefit analyses, their true impact extends across the entire transportation network. Dredging one segment can unlock capacity across multiple routes, while ignoring another segment can constrain an entire flow. This system-wide interdependence is frequently overlooked in practice. As a result, existing planning methods often underestimate the value of certain dredging investments and fail to fully capture their downstream or network-wide effects.

A central motivation of this research is to address a recurring shortcoming in how dredging and lock maintenance projects are evaluated and prioritized. Traditionally, these investments are assessed using simplified, localized cost-benefit logic, for example, calculating how much it costs to dredge a specific segment and estimating direct savings from reduced delay or increased throughput at that segment alone. However, this approach fails to account for the broader interdependencies in the inland waterway network. Improvements at one location can unlock higher-capacity routes, reduce system-wide shipping costs, and enhance the flow of multiple commodity streams. Conversely, deferring maintenance on a single critical segment may block entire routes or force traffic onto suboptimal alternatives.

To address this, our research reframes the problem from one of local optimization to system-wide performance maximization. Instead of selecting projects based solely on individual return, we model how local actions (e.g., dredging, lock repair) affect the overall navigability and freight throughput of the network. Our goal is to allocate a limited maintenance budget in a way that delivers the greatest systemic benefit, in terms of reduced total shipping costs, improved reliability, and robust flow across all origin-destination (OD) pairs.

Mathematically, we formalize this goal through an objective function that minimizes the total system-wide shipping cost, computed based on route availability, draft depth, vessel counts, delay costs, and maintenance decisions. This represents a shift away from isolated cost-saving calculations and toward a holistic view of freight movement efficiency.

In doing so, this study also corrects several technical flaws observed in earlier optimization models, including improper depth logic, unrealistic assumptions about initial conditions, and one-time-only decision-making. By incorporating more accurate physical relationships, multi-year decision horizons, and stochastic shoaling effects, the models developed here aim to better reflect real-world challenges and produce more effective, data-driven budget allocation strategies for inland waterway maintenance.

This study addresses that gap by developing models that measure dredging and lock maintenance not merely through isolated improvements, but by examining their effects on overall system throughput and freight movement efficiency. In particular, this research tests how much more effective budget allocation can be when projects are selected based on their system-level impact rather than local conditions alone.

To do so, we begin by identifying and correcting limitations in an existing optimization model previously used to guide budget decisions for inland waterway maintenance. We then propose two improved models: one that makes a single-year decision using more accurate physical and logical assumptions, and another that extends the framework to a two-year adaptive planning horizon. Both models are tested using realistic data from the Ohio River Basin to assess their effectiveness in reducing system-wide shipping costs under various budget and uncertainty scenarios.

Our ultimate objective is to demonstrate that better modeling, modeling that reflects actual operating conditions, multi-year dynamics, and interdependencies, can lead to significantly better outcomes for freight efficiency, cost savings, and infrastructure resilience.

1.2 Literature Review

The maintenance of inland waterways plays a vital role in sustaining the functionality of multimodal freight transportation networks. Inland waterways, which consist of rivers, locks, dams, and navigation channels, are essential for efficient freight movement, offering a cost-effective and safe alternative to road and rail transport [20]. However, the natural process of shoaling, where sediment accumulation affects navigability, necessitates continuous dredging operations and lock maintenance to ensure the system's reliability. Budget allocation for these maintenance activities must consider both short-term operational needs and long-term infrastructure sustainability, especially when addressing the stochasticity inherent in the shoaling process [18].

A well-designed budget allocation model must integrate both dredging and lock maintenance to optimize the performance of inland waterways. The selection and prioritization of maintenance projects have been extensively studied, with emphasis on single-year decision-making frameworks. For example, traditional optimization models focus on maximizing tonnage throughput while minimizing costs in a single planning cycle [7]. However, these models often fail to consider intertemporal dependencies, where the maintenance decision in one year directly influences the subsequent year's conditions. Recent studies have proposed multi-year planning frameworks to address this issue. Bian et al. [9] developed a multi-year dredging prioritization model, demonstrating that such an approach can lead to a 27.27% reduction in annual budget allocation compared to single-year plans.

While budget allocation for maintenance dredging has been explored, most existing studies do not explicitly account for the stochastic nature of shoaling. Shoaling is influenced by multiple unpredictable factors such as storm surges, river flow rates, and sediment transport dynamics [24]. Addressing this uncertainty, stochastic optimization models have been employed to develop robust maintenance strategies. Ratick et al. [22] introduced a risk-based dredging decision model that minimizes expected costs by considering stochastic sediment accumulation. Similarly, a stochastic programming approach was used by Elcheikh et al. [15] to evaluate the cost of uncertainty in waterway maintenance, proposing multi-scenario models to mitigate potential failures.

Recent studies emphasize the need for integrated decision-making models that jointly optimize dredging and lock maintenance. Traditionally, these two activities have been considered separately; however, integrated models have been shown to improve efficiency and budget utilization. Ghorbani et al. [16] proposed a two-stage mixed integer non-linear programming model to optimize maintenance project selection by balancing maintenance costs and expected failure risks. This model considers system reliability over multiple planning periods, highlighting the importance of a multi-year approach. Similarly, Mahmoudzadeh et al. [17] developed a decision-support framework that accounts for multimodal transportation effects in waterway maintenance planning.

The initial depth of navigation channels is a critical but often overlooked factor in budget allocation models. Most previous studies assume uniform sedimentation rates, ignoring the heterogeneity of sediment deposition along different waterway segments. However, research has shown that variable initial depths significantly impact maintenance scheduling and cost estimation. Ahadi et al. [5] emphasized that accounting for initial depths when optimizing maintenance decisions improves long-term planning. Similarly, Dunkin et al. [12] developed a shoaling analysis tool to predict sedimentation trends, demonstrating that integrating initial bathymetric data into budget models enhances decision-making accuracy. Curlee et al. [11] further analyzed economic foundations that impact navigation investment decisions, highlighting the long-term financial benefits of improved budget allocation strategies. Additionally, Bhurtyal et al. [8] introduced a two-stage stochastic optimization model for port infrastructure planning, emphasizing the importance of uncertainty modeling in waterway maintenance.

From an optimization perspective, multi-year budget allocation falls within the domain of stochastic programming and integer programming approaches. Mixed-integer linear programming (MILP) models have been widely used for maintenance decision-making under uncertainty. Nur et al. [19] proposed a multi-period mixed-integer programming model for inland waterway port operations, optimizing both short-term operational decisions and long-term investment strategies. In offshore maintenance planning, Schrotenboer et al. [23] developed a stochastic MILP framework to optimize offshore wind farm maintenance, demonstrating the effectiveness of probabilistic approaches in scheduling maintenance tasks under uncertain conditions. Similarly, Wang and Schonfeld [25] explored scheduling interdependent waterway projects through simulation and genetic optimization, reinforcing the importance of adaptive decision-making techniques in infrastructure management.

Two-stage stochastic optimization models have also been explored for waterway maintenance budget allocation. In railway infrastructure maintenance, D'Ariano et al. [13] formulated an integrated scheduling model for train operations and track maintenance, demonstrating the advantage of synchronized decision-making in transportation networks. Similarly, in dredging projects selection, a two-stage stochastic programming model was developed to optimize maintenance planning under uncertain shoaling conditions [3]. This approach considers recourse actions, allowing decision-makers to adjust maintenance plans dynamically based on real-time sedimentation data. Further, Aghamohammadghasem et al. [4] applied deep reinforcement learning to optimize preventive maintenance strategies for inland waterway systems, showcasing the potential of Artificial Intelligence (AI)-driven methodologies.

The integration of machine learning and artificial intelligence in maintenance decision-making has gained traction in recent years. Deep reinforcement learning has been applied in infrastructure asset management, showing promising results in optimizing maintenance schedules [10]. In inland waterways, Asborno and Hernandez [6] introduced a stochastic modeling framework to quantify freight flows through waterways, incorporating historical vessel movement data to improve cargo routing decisions. These AI-driven approaches provide new opportunities for refining budget allocation models by enhancing predictive capabilities and scenario-based planning. Rahbaralam et al. [21] leveraged machine learning and survival analysis to forecast pipeline failures, demonstrating applicability to waterway asset management.

Furthermore, advances in multi-objective optimization techniques have allowed researchers to incorporate economic trade-offs in maintenance decision-making. Studies have explored balancing the economic benefits of dredging against potential ecological impacts, ensuring efficient waterway operations [14]. Simulation-based approaches, such as those developed by Aghamohammadghasem et al. [3], offer valuable insights into managing natural events and mitigating adverse effects on aquatic ecosystems.

In summary, while extensive research has been conducted on dredging project selection, stochastic modeling, and maintenance optimization, existing studies have largely focused on single-year planning frameworks and have often overlooked the impact of initial depth and intertemporal dependencies. Our study seeks to bridge these gaps by developing a multi-year budget allocation model that explicitly captures stochastic shoaling effects, initial depth variations, and the combined impact of dredging and lock maintenance. By integrating stochastic optimization, machine learning-based forecasting, and integer programming techniques, this work aims to enhance the resilience and cost-effectiveness of waterway maintenance planning.

2 Methodological Approach

The maintenance and operation of inland waterways are critical for ensuring the efficiency of freight transportation. These waterways provide an essential alternative to road and rail transport, offering cost-effective freight movement. However, the natural process of shoaling, where sediment accumulates and reduces navigable depth, combined with aging lock infrastructure, requires continuous maintenance efforts.

Effective budget allocation for waterway maintenance is challenging due to the need to balance dredging and lock improvement costs while operating under financial constraints. An optimal budget allocation model must consider the stochastic nature of shoaling, the reliability of aging infrastructure, and the necessity of ensuring continuous navigability. Previous research has attempted to address this problem using optimization techniques, but existing models have several limitations. This study aims to refine these models by addressing their deficiencies and proposing a more robust formulation.

The models developed in this study are designed to move beyond traditional, segment-level evaluation strategies and instead adopt a system-wide optimization perspective. In real-world planning, dredging and lock maintenance projects are often prioritized based on localized return-on-investment metrics, for instance, estimating shipping delay reductions at a single lock or calculating the cost per ton of sediment removed at one segment. However, such methods overlook the fact that waterway infrastructure operates as an interconnected system: a bottleneck at one point can affect multiple routes and origin-destination pairs, while an improvement elsewhere may yield cascading benefits. Our models seek to capture these broader interactions explicitly, optimizing decisions not for isolated outcomes but for their impact on total network performance. This is achieved by formulating an objective function that minimizes total system-wide shipping cost, taking into account vessel requirements, draft constraints, delay penalties, and multi-route commodity flows. In doing so, we ensure that every maintenance action is evaluated not just on its local effect, but on its contribution to system-wide freight efficiency.

Before presenting the modeling frameworks in detail, we first introduce the notations, variables, and parameters used consistently throughout all formulations. These definitions provide a unified foundation for understanding the mathematical structures and decision-making components of each model variant.

2.1 Model Inputs and Definitions

2.1.1 Notations

L = Set of all locks
W = Set of all origin-destination pairs
R = Set of all routes
$R(m)$ = Set of routes on OD $m, R(m) \subset R$
S = Set of all waterway segments
P = Set of all stages, $t \subset P$
$S(r)$ = Set of waterway segments on route $r, S(r) \subset S$
Z = Integer set $\{0, 1, 2, \ldots, 13\}$,
Discrete dredging depth of projects allowed with 13 ft being the full depth proposed.
N = Integer set $\{1, 2, 3, 4, 5, 6\}$,
The lock/dam improvement level.
H = Integer set $\{0, 20, 40, 60, 80, 100\}$,
The lock/dam improvement value according to levels.
For example, level 5 maintenance carries out 80% of the proposed full amount.

2.1.2 Variables

$$d_i^k = \begin{cases} 1, & \text{If segment } i \text{ is dredged by } k \text{ feet, } k \subset Z \\ 0, & \text{otherwise} \end{cases}$$

$$w_{j,n} = \begin{cases} 1, & \text{If lock } j \text{ is selected for maintenance (when the degree of } h_n \text{ is increased)} \\ 0, & \text{otherwise} \end{cases}$$

$$x_r^{k,1} = \begin{cases} 1, & \text{If all the segments on route } r \text{ are dredged by } k \text{ feet or more in the first stage} \\ 0, & \text{otherwise} \end{cases}$$

$$x_r^{k,2} = \begin{cases} 1, & \text{If all the segments on route } r \text{ remain } k \text{ feet or more in the second stage} \\ 0, & \text{otherwise} \end{cases}$$

$$A_r^{(q,1)} = \begin{cases} 1, & \text{If all the segments on route } r \text{ have } q \text{ feet depth or more in the first stage} \\ 0, & \text{otherwise} \end{cases}$$

$$A_r^{(q,2)} = \begin{cases} 1, & \text{If all the segments on route } r \text{ have } q \text{ feet or more depth in the second stage} \\ 0, & \text{otherwise} \end{cases}$$

l_j = Amount of improvement (i.e., maintenance) determined on lock j (in percentage), $\quad l_j \subset H$

C_j = Cost of maintenance of lock j

y_j = Total reduction of expected delay at lock j using the linear approximation in the first stage

$C_r^{\max 1}$ = Shipping cost of route r in the first stage

$C_r^{\max 2}$ = Shipping cost of route r in the second stage

2.1.3 Parameters

C_i^k = Cost of dredging segment i by k feet
B_r^q = The tonnage capacity of route r with q feet depth
N_r^k = The required number of vessels to meet the demand after dredging route r by k feet
N_r^q = The required number of vessels to meet the demand on route r with q feet depth
$P_{r,m}$ = The portion of the tonnage of route r allocated to the total OD of m,
where $\sum_{m \in W} P_{r,m} = 1, \forall r \in R$. Preset volume split between alternative routes.
c_r = Average shipping cost per vessel on route r
D_m = The freight demand on OD m
b_n = Cost of maintenance level n
β_j = Unit cost of improvement for lock j
V = Delay value (i.e., cost) per hour per vessel
h_n = Alternative amount of improvement on a lock. It is one of the values in H,
e.g., $h_n \subset H$, where $n \in N$. Here $h_1 = 0, h_2 = 20, \ldots, h_6 = 100$
$f_j(h_n)$ = The amount of delay reduction for lock j resulting from level n maintenance
T = Total budget available for all the maintenances
IR = Inflation Ratio
M = Big M, a large number
U = Upper limit of the mean reduced delay of all locks.
It may be a large enough number to make the formulation work.
Dy_j = Existing delay of the lock j at its current state.

2.2 Brief review of prior model

A previously developed budget allocation model aimed to minimize the total cost of shipping and maintenance over a two-year horizon while ensuring sufficient navigation depth. However, several flaws were identified in its formulation. These issues included errors in constraint logic, incorrect depth allocation methods, and improper handling of decision variables.

Objective Function:

$$\min \sum_{r \in R} \left(C_r^{\max 1} + C_r^{\max 2} \right) \tag{1}$$

Constraints:

$$\sum_{i \in S} \sum_{k \in Z} d_i^k C_i^k + \sum_{j \in L} C_j \leq T \tag{1.1}$$

$$\sum_{k \in Z} d_i^k \leq 1 \quad (\forall i \in S) \tag{1.2}$$

$$\sum_{k \in Z} x_r^{(k,1)} = 1 \quad (\forall r \in R) \tag{1.3}$$

$$\sum_{k \in Z} x_r^{(k,2)} = 1 \quad (\forall r \in R) \tag{1.4}$$

$$\sum_{k \in Z} k x_r^{(k,1)} \leq \sum_{k \in Z} k d_i^k \quad (\forall r \in R, \forall i \in S(r)) \tag{1.5}$$

$$\sum_{k \in Z} k x_r^{(k,2)} \leq \sum_{k \in Z} E(k) d_i^k \quad (\forall r \in R, \forall i \in S(r)) \tag{1.6}$$

$$\sum_{r \in R(m)} \sum_{k \in Z} x_r^{k,1} B_r^k P_{r,m} = D_m \quad (\forall m \in W) \tag{1.7}$$

$$\sum_{r \in R(m)} \sum_{k \in Z} x_r^{k,2} B_r^k P_{r,m} = D_m \quad (\forall m \in W) \tag{1.8}$$

$$\sum_{k \in Z} \{ x_r^{(k,1)} N_r^k c_r + \sum_{j \in L} (U - y_j) N_r^k V + (x_r^{(k,1)} - 1) M \} \leq C_r^{\max 1} \quad (\forall r \in R) \tag{1.9}$$

$$\sum_{k \in Z} \{ x_r^{(k,2)} N_r^k c_r + \sum_{j \in L} (U - y_j) N_r^k V + (x_r^{(k,2)} - 1) M \} \leq C_r^{\max 2} \quad (\forall r \in R) \tag{1.10}$$

$$y_j = \sum_{n \in N} w_{j,n} f_j(h_n) \quad (\forall j \in L, \forall h_n \in H) \tag{1.11}$$

$$l_j = \sum_{n \in N} w_{j,n} h_n \quad (\forall j \in L, \forall h_n \in H) \tag{1.12}$$

$$\sum_{n \in N} w_{j,n} = 1 \quad (\forall j \in L) \tag{1.13}$$

$$C_j = \begin{cases} \beta_j l_j \\ \beta_j l_j + \sum_{n \in N} w_{j,n} h_n b_n \end{cases} \qquad (\forall j \in L) \tag{1.14.1 or 1.14.2}$$

$$d_i^k, w_{j,n}, x_r^{(k,1)}, x_r^{(k,2)} \in \{0,1\} \quad (\forall k \in Z, \forall i \in S, \forall j \in L, \forall n \in N) \tag{1.15}$$

$$C_j, l_j, y_j, C_r^{\max 1}, C_r^{\max 2} \geq 0 \quad (\forall j \in L, \forall r \in R) \tag{1.16}$$

Constraint (1.1) limits the total cost of dredging and lock/dam maintenance to the available budget. The lock/dam maintenance cost is associated with the total amount of improvement l, which is evaluated in Constraints (1.11)–(1.14), and the dredging cost is calculated with the indicator variable d. Constraint (1.2) prescribes that there can only be one dredging depth per segment. Constraint (1.3) states that there is only one depth increase from dredging in the channel on each path of OD flow. Constraint (1.4) is similar to (1.3), but for year two after shoaling. Constraints (1.5) mandates that the effective, increased depth of each path from dredging be determined by the dredging depth of each segment in the first stage, essentially meaning that the smallest depth increase among the segments along a route becomes the depth increase of the entire route. Constraint (1.6) is similar to (1.5), but is based on the remaining depth after shoaling in stage two. The dredging depth in the first stage is selected to minimize the expected value of the total cost over the period of two years. The expected depth is calculated based on historical data and the probability of shoaling after dredging. Constraints (1.2)–(1.6) prescribe a relationship that an entire route is dredged to depth k if and only if the smallest dredging depth of all segments along this route is k. Constraints (1.7) and (1.8) ensure that the demand for each OD commodity stream can be met. Constraints (1.9) and (1.10) specify the cap of the total cost on each stage to be minimized in the objective function. The cost of each route is calculated based on the number of vessels of according size allowed on the route in order to meet the demand. Here the number of vessels N_r^k is the total capacity B_r^k divided by the vessel capacity, both N_r^k and N_r^k being constant for given k and r. The vessel capacity and per vessel cost c_r here are approximate estimates based on subjective judgment by using prevailing vessel size available to each draft depth available based on experiences. It should be mentioned that the number of vessels required to deliver the demand are relatively large for low drafting depths, so these four constraints work altogether to make sure that the demand is met by lowering the shipping costs. Constraints (1.11)–(1.14) implies a relationship between maintenance costs and delays of the dam. Constraint (1.13) only allows to choose one of the maintenance levels for each lock or dam. Constraint (1.11) translates a level of maintenance/improvement to the exact percentage, such as 40 percent improvement from the discrete set H. Constraint (1.12) translates the percentage of improvement at a lock/dam into the expected waiting time/delay cost reduction (in time) per vessel. The delay reduction is first calculated in hours before converting into dollars by multiplying it into the delay cost parameter available in Constraints (1.9) and (1.10). The relationship between the level of maintenance at each dam and the vessel delay reduction depends on the dam failure probability. A failure may be simply a shutdown for a short period of time due to needed repair to some failed components. The delay may also be due to reduced capacity for lack of sufficient maintenance. Constraints (1.14.1) and (1.14.2) are two alternatives for translating the magnitude of improvement into unit improvement cost for each particular lock/dam. Constraint (1.14.1) uses a linear function at a fixed rate while the alternative, (1.14.2) adopts a linear way to approximate an increasing rate of cost with maintenance. Each time the model is run, only one of the two constraints is chosen. The rationale for exploring (1.14.2) is that for larger scale improvement, larger equipment may be needed to rent and use, therefore incurring larger cost per unit improvement. Constraints (1.15) and (1.16) are the standard binary and non-negativity constraints.

The limitations identified in the old model necessitated a new formulation to ensure more accurate and effective budget allocation for inland waterway maintenance. Key modifications include incorporating initial depths of segments to determine effective dredging needs, optimizing based on navigational draft rather than dredging depth, and correcting errors in constraint formulation which were incorrectly implemented in the previous model.

2.3 Development of the New Model

The new model that we developed follows a similar two-stage stochastic structure, but with improved formulations to reflect real-world constraints and decision-making processes more accurately. Below is the full formulation of the new model, including its objective function, and constraints.

Objective Function:

$$\min \sum_{r\in R} \left(C_r^{\max 1} + C_r^{\max 2}\right) \tag{2}$$

Constraints:

$$\sum_{i\in S}\sum_{k\in Z} d_i^k C_i^k + \sum_{j\in L} C_j \le T \tag{2.1}$$

$$\sum_{k\in Z} d_i^k \le 1 \tag{2.2}$$

$$\sum_{q\in Z} A_r^{(q,1)} = 1 \tag{2.3}$$

$$\sum_{q\in Z} A_r^{(q,2)} = 1 \tag{2.4}$$

$$\sum_{q\in Z} qA_r^{(q,1)} \le \sum_{k\in Z} (kd_i^k) + R_i \tag{2.5}$$

$$4 \le kd_i^k + R_i \le 13 \tag{2.5.1}$$

$$\sum_{q\in Z} qA_r^{(q,2)} \le \sum_{k\in Z} E(kd_i^k + R_i) \tag{2.6}$$

$$4 \le \sum_{k\in Z} E(kd_i^k + R_i) \le 13 \tag{2.6.1}$$

$$A_r^{(q,1)} N_r^q c_r + \sum_{j\in L} (Dy - y_j) N_r^q V + (A_r^{(q,1)} - 1)M \le C_r^{\max 1} \tag{2.7}$$

$$A_r^{(q,2)} N_r^q c_r + \sum_{j\in L} (Dy - y_j) N_r^q V + (A_r^{(q,2)} - 1)M \le C_r^{\max 2} \tag{2.8}$$

$$y_j = \sum_{n\in N} w_{j,n} f_j(h_n) \tag{2.9}$$

$$l_j = \sum_{n\in N} w_{j,n} h_n \tag{2.10}$$

$$\sum_{n\in N} w_{j,n} = 1 \tag{2.11}$$

$$C_j = \beta_j l_j \tag{2.12}$$

$$d_i^k, w_{j,n}, A_r^{(q,1)}, A_r^{(q,2)} \in \{0,1\} \tag{2.13}$$

$$C_j, l_j, y_j, C_r^{\max 1}, C_r^{\max 2} \geq 0 \tag{2.14}$$

The previous model included constraints related to land transportation. However, since this study focuses exclusively on waterway transportation, constraints associated with land transportation were removed. By solving a scenario that considers only waterway maintenance, we can effectively demonstrate the improvements introduced in the new model without unnecessary complications.

Constraint (2.1) limits the total cost of dredging and lock/dam maintenance to the available budget. The lock/dam maintenance cost is associated with the total amount of improvement l, which is evaluated in Constraints (2.9)–(2.12), and the dredging cost is calculated with the indicator variable d. Constraint (2.2) prescribes that there can only be one dredging depth per segment. Constraint (2.3) states that there is only one depth after dredging in the channel on each path of OD flow. Constraint (2.4) is similar to (2.3), but for year two after shoaling. Constraints (2.5) mandates that the effective, draft of each path be determined by summation of the dredging depth of each segment in the first stage and its initial depth, essentially meaning that the smallest draft among the segments along a route becomes the draft of the entire route. Constraint (2.6) is similar to (2.5) but is based on the remaining draft after shoaling in stage two. The dredging depth in the first stage is selected to minimize the expected value of the total cost over the period of two years. The expected draft is calculated based on historical data and the probability of shoaling after dredging. Constraints (2.2)–(2.4), and (2.5), (2.6) prescribe a relationship that an entire route depth q if and only if the smallest depth of all segments along this route after dredging is q. Constraint (2.5.1) mandates the draft of each segment in the first stage can not exceed its lower and upper bounds. Constraint (2.6.1) is similar to (2.5.1) but for second stage. Constraints (2.5.1) and (2.6.1) are conditional constraints for when it is required to have the structure of new model be as close as possible to old model but generally are excluded when searching for the optimum solution for new model. Constraints (2.8) and (2.9) specify the cap of the total cost on each stage to be minimized in the objective function. The cost of each route is calculated based on the number of vessels of according size allowed on the route. The per vessel cost cr here is approximate estimate based on subjective judgment by using prevailing vessel size available to each draft available based on experience. It should be mentioned that the number of vessels required to deliver the demand are relatively large for low drafting depths, so these four constraints work altogether to make sure that the demand is met by lowering the shipping costs. Constraints (2.9)–(2.12) implies a relationship between maintenance costs and delays of the dam. Constraint (2.11) only allows to choose one of the maintenance levels for each lock or dam. Constraint (2.10) translates a level of maintenance/improvement to the exact percentage, such as 40 percent improvement from the discrete set H. Constraint (2.9) translates the percentage of improvement at a lock/dam into the expected waiting time/delay cost reduction (in time) per vessel. The delay reduction is first calculated in hours before converting into dollars by multiplying it into the delay cost parameter available in Constraints (2.7) and (2.8). The relationship between the level of maintenance at each dam and the vessel delay reduction depends on the dam failure probability. A failure may be simply a shutdown for a short period of time due to needed repair to some failed components. The delay may also be due to reduced capacity for lack of sufficient maintenance. Constraint (2.12) translates the magnitude of improvement into unit improvement cost for each particular lock/dam. Constraints (2.13) and (2.14) are the standard binary and non-negativity constraints.

Although the new model introduces significant improvements, it retains the single-year decision-making approach of its predecessor. While it accounts for future conditions, it only makes one decision at the beginning of the planning period and observes its impact in subsequent years.

To further enhance the model, we propose an expanded version that allows for two-year decision-making. Instead of making a single decision and assessing its impact, this formulation will allow decision-makers to adjust maintenance plans dynamically across multiple years.

This multi-year approach will be tested using a similar example to compare its performance against the new model. If the expanded model demonstrates superior results, it will justify replacing the new model, paving the way for future research into longer planning horizons (10–20 years).

2.4 Expanded Model Formulation

Objective Function:

$$\min \sum_{r\in R} \left(C_r^{\max 1} + C_r^{\max 2}\right) \tag{3}$$

Constraints:

$$\sum_{t\in P} (IR)^t \left(\sum_{i\in S} \sum_{k\in Z} d_i^{(k,m)} C_i^k + \sum_{j\in L} C_j^t \right) \leq T \tag{3.1}$$

$$\sum_{k\in Z} d_i^{(k,t)} \leq 1 \quad (\forall t \in P) \tag{3.2}$$

$$\sum_{q\in Z} A_r^{(q,t)} = 1 \quad (\forall t \in P) \tag{3.3}$$

$$\sum_{q\in Z} q A_r^{(q,1)} \leq \sum_{k\in Z} \left(k d_i^{(k,1)} \right) + R_i \quad (\forall r \in R, \forall i \in S(r)) \tag{3.4}$$

$$\sum_{q\in Z} q A_r^{(q,2)} \leq \sum_{k\in Z} E(k d_i^{(k,1)} + R_i) + \sum_{k\in Z} k d_i^{(k,2)} \quad (\forall r \in R, \forall i \in S(r)) \tag{3.5}$$

$$A_r^{(q,1)} N_r^q c_r + \sum_{j\in L} (Dy - y_i^1) N_r^q V + (A_r^{(q,1)} - 1) M \leq C_r^{\max 1} \quad (\forall r \in R, \forall q \in Z) \tag{3.6}$$

$$A_r^{(q,2)} N_r^q c_r + \sum_{j \in L} (Dy - y_i^1 - y_i^2) N_r^q V + (A_r^{(q,2)} - 1) M \leq C_r^{\max 2} \quad (\forall r \in R, \forall q \in Z) \tag{3.7}$$

$$y_j^t = \sum_{n \in N} w_{j,n}^t f_j(h_n) \quad (\forall j \in L, \forall h_n \in H, \forall t \in P) \tag{3.8}$$

$$l_j^t = \sum_{n \in N} w_{j,n}^t h_n \quad (\forall j \in L, \forall h_n \in H, \forall t \in P) \tag{3.9}$$

$$\sum_{n \in N} w_{j,n}^t = 1 \quad (\forall j \in L, \forall t \in P) \tag{3.10}$$

$$C_j^t = \beta_j l_j^t \quad (\forall j \in L, \forall t \in P) \tag{3.11}$$

$$d_i^{(k,t)}, w_{j,n}^t, A_r^{(q,t)} \in \{0,1\} \quad (\forall k \in Z, \forall r \in R, \forall i \in S, \forall j \in L, \forall n \in N, \forall t \in P) \tag{3.12}$$

$$C_j^t, l_j^t, y_i^t, C_r^{\max 1}, C_r^{\max 2} \geq 0 \quad (\forall j \in L, \forall r \in R, \forall t \in P) \tag{3.13}$$

The objective of this expansion is to enable adaptive decision-making across both years rather than committing all resources upfront. By introducing this flexibility, we aim to quantify the impact of two-year planning compared to a single-year approach, determining whether the additional complexity and computational effort are justified by meaningful improvements or if the benefits remain marginal, rendering a one-year framework sufficient.

In the third model, the total maintenance budget is still allocated across two years, but unlike the previous models, the decision-making is split into two stages. The first-year decisions are made at the beginning of the planning horizon, while the second-year decisions are deferred and made conditionally based on predicted shoaling outcomes derived from the remaining depth after the first year. To more realistically reflect the cost of delaying maintenance actions, we introduce an inflation ratio that penalizes second-year maintenance costs. This addition captures a common challenge in infrastructure planning, that waiting to act often increases costs, and allows the model to represent a practical trade-off between early, potentially less-informed decisions and later, more tailored but costlier interventions.

3 Results and Findings

In this section, we present a comprehensive evaluation of the developed optimization models by analyzing their numerical performance, computational outcomes, and behavior under different input configurations. We begin with a description of the test case setup and then explore comparative performance in terms of cost-efficiency, sensitivity to data uncertainty, and ability to minimize total expenditures under varying budget scenarios.

3.1 Test Case

This model is tested using the data collected through NCF and eHydro for the Ohio River Basin. The Ohio River system plays an essential role in freight movement in the U.S. and is the single busiest waterway in the Mississippi River System (MRS). It should also be said that the traffic going through MRS and the Great Lakes together covers more than 33% of all waterborne freight traffic by weight [2].

In this study, we focus on the Ohio River, located in USACE Great Lakes and Ohio River Division (LRD). This division is comprised of seven USACE Districts, namely Buffalo, Chicago, Detroit, Huntington, Louisville, Nashville, and Pittsburgh Districts.

The Ohio River is a 981-mile river flowing from Pittsburgh, Pennsylvania, to its mouth on the Mississippi River. It is a key U.S. commercial waterway for the transport of bulk coal and grain along the U.S. This study focuses on the portion of 428.7 miles of the Ohio River located at USACE's Louisville (CELRL) and Huntington (CELRH) Districts, subdivided into 27 NCF reaches. Figure 1 shows the geographic layout of the river.

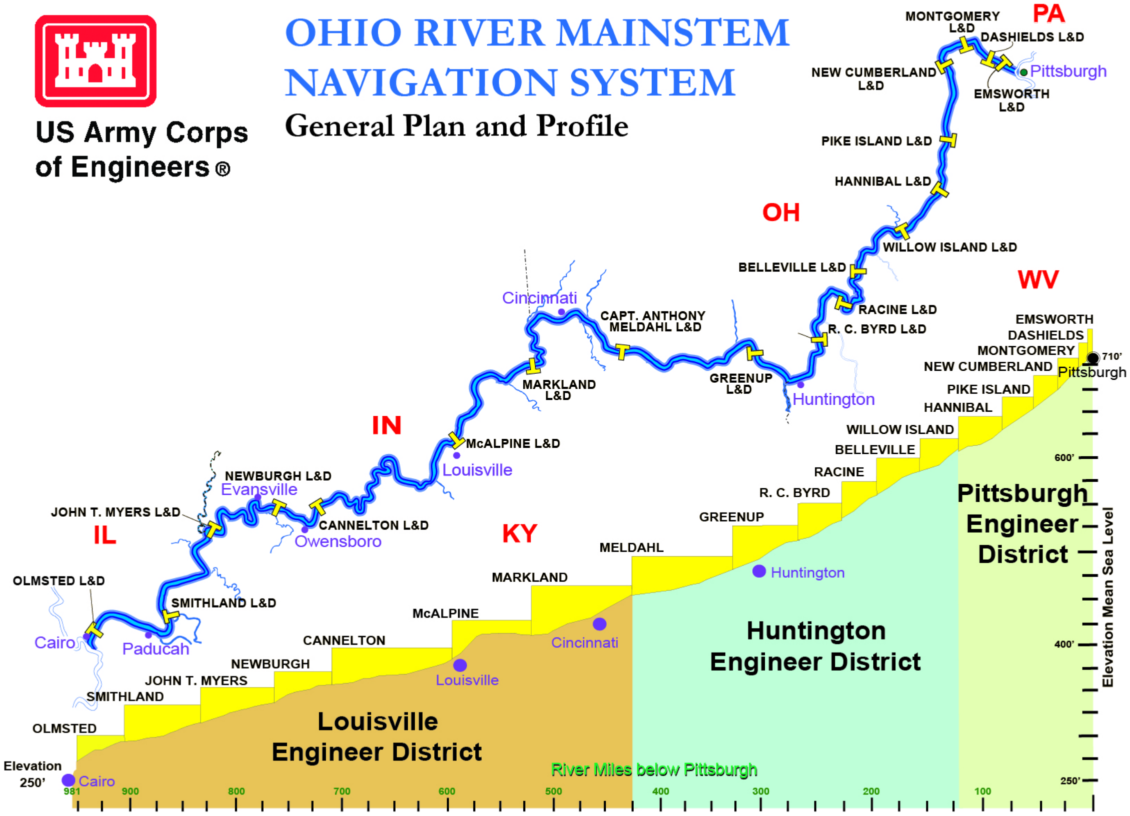

Figure 1: The Ohio River Corridor

Source: [1]

3.2 Comparative Analysis of Dredging Costs

The primary objective of this study is to evaluate how effectively the new model minimizes dredging expenditures relative to available budget constraints, without compromising navigational service levels. The results indicate a substantial reduction in dredging costs when employing the new model compared to the old model. Specifically, the new model achieves a cost reduction ranging from 30% to 40% under comparable scenarios. This significant decrease underscores the efficacy of the new model in optimizing resource allocation for maintenance activities.

To elucidate the relationship between budget constraints and cost savings, we analyzed scenarios with varying budget levels of availability. Since actual budget availability is typically determined by external decision-makers and was unknown in our case, we assumed a benchmark for full funding. Specifically, we calculated the total cost required to fully support all potential projects, assuming the maximum improvement possible for each (e.g., dredging every segment to 13 feet depth and applying full lock maintenance), and defined this value as the 100% budget level. In reality, we rarely receive enough funds to support all projects to their fullest extent. Therefore, to reflect more realistic conditions, we also analyzed scenarios with partial budget availability, such as 30% or 40% of the full budget. This setup allows us to investigate how the models perform under constrained funding.

The findings shown in Table 1 reveal that under more stringent budget conditions, the new model's efficiency becomes even more pronounced, with cost reductions reaching up to 38.5%. Conversely, in scenarios with higher budget allocations, the cost savings stabilize around 31.2%. This trend suggests that the new model is particularly advantageous when financial resources are limited, ensuring optimal utilization of available funds.

Table 1: Test results of the second model with varying budget

Budget scenario	Allocated dredging budget for the Old Model ($)	Allocated dredging budget for the New Model ($)	Improvement
30.0%	507902.1	312464.5	38.5%
40.0%	571144.2	389039.4	31.9%
50.0%	573655.8	393080.9	31.5%
60.0%	577249.4	397303.6	31.2%
70.0%	576128.5	394303.3	31.6%
80.0%	579975.5	400524.7	30.9%
90.0%	575628.5	394499.1	31.5%
100.0%	577870.4	397746.1	31.2%

3.3 Sensitivity to Initial Depth Variations

Accurate data on the initial depths of waterway segments was not available for this study, which posed a challenge in evaluating the impact of depth variations on maintenance strategies. To address this, we performed a sensitivity analysis by generating multiple simulation scenarios in which the initial depth values for each waterway segment were randomly assigned within a plausible range. For each randomized configuration, the model was solved independently to observe how variations in input conditions would influence overall performance.

The results, depicted in Figure 2, demonstrate that the cost reduction achieved by the new model remains substantial across all randomized runs. The shaded bands in the figure represent error margins around the mean values, confirming the consistency of performance. This robustness is important for real-world applications, where data limitations are common, and suggests that the model's recommendations are reliable even in the presence of input uncertainty.

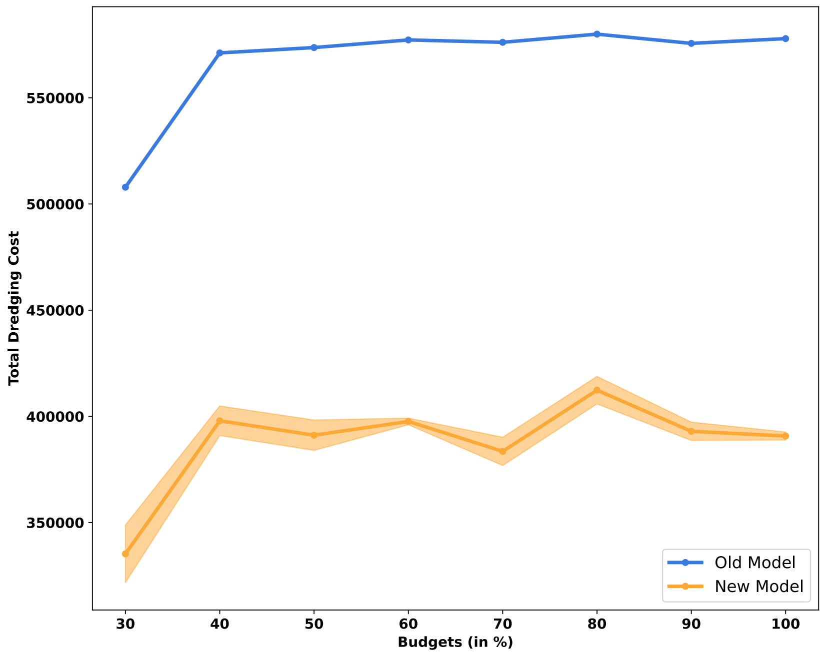

Figure 2: Comparison of old and new models' dredging cost

4 Impacts and Benefits of Implementation

In this section, we examine the broader operational and economic implications of the improved models. We focus on how the implementation of the second and third models contributes to long-term shipping cost savings, dynamic decision-making across a two-year horizon, and resilience under varying inflationary and budgetary pressures.

4.1 Impact on Shipping Costs Over a Two-Year Period

Beyond immediate maintenance costs, an effective budget allocation model should contribute to long-term reductions in operational expenses, particularly shipping costs. A well-maintained waterway network allows for smoother navigation, reduces delays, and enhances freight transport efficiency.

The results indicate that the old model does contribute to a reduction in shipping costs over the two-year period following maintenance interventions. Figures 3 to 5 present the impact of the old model on shipping costs for different available budgets, showing that despite its limitations, it still led to improvements in operational efficiency. While the new model offers a more efficient approach, the performance of the old model demonstrates that structured maintenance planning, even with its prior limitations, plays a critical role in enhancing the cost-effectiveness of inland waterway transportation. However, the enhanced models, particularly the third model, further amplified these benefits by dynamically responding to sedimentation changes over two years.

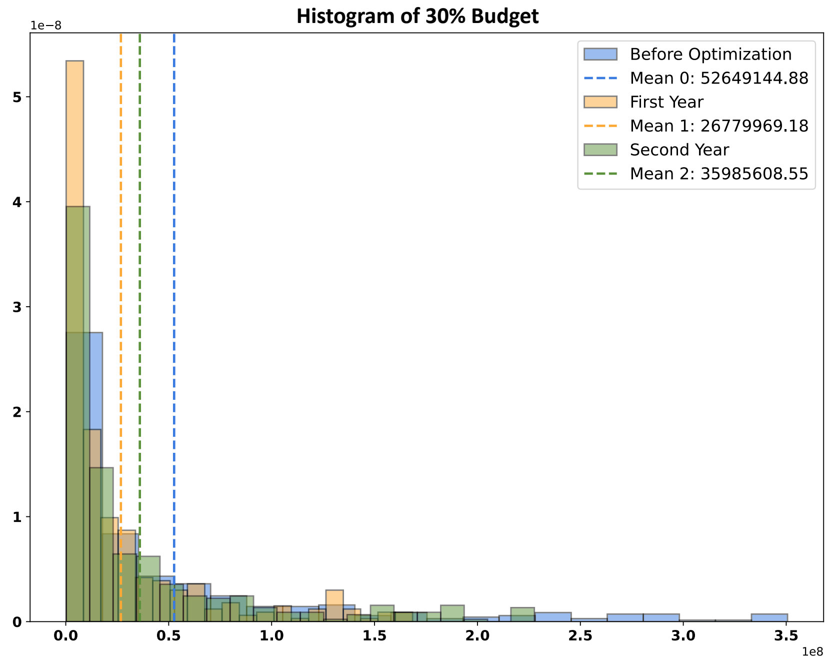

Figure 3: Histogram of Shipping Costs for 30% of the Total Budget (Density)

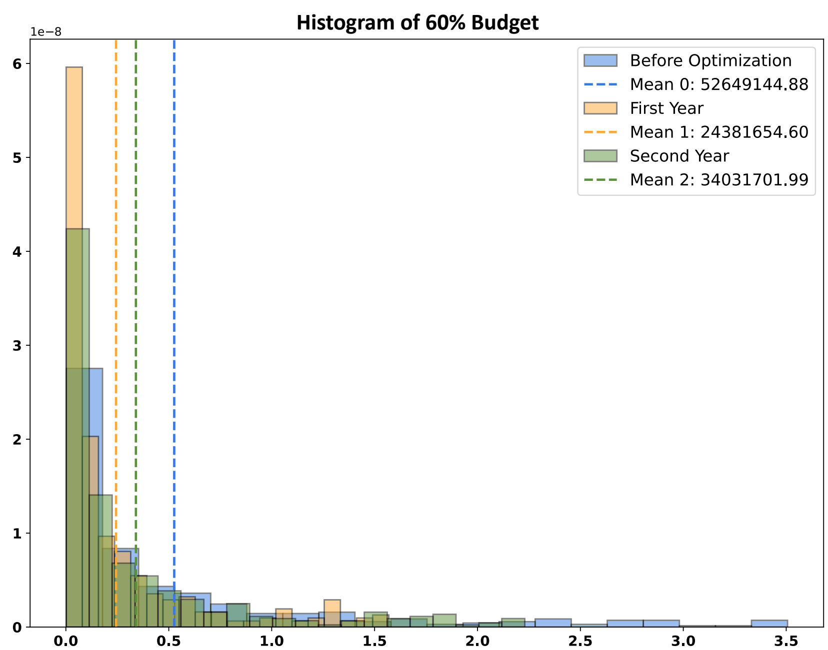

Figure 4: Histogram of Shipping Costs for 60% of the Total Budget (Density)

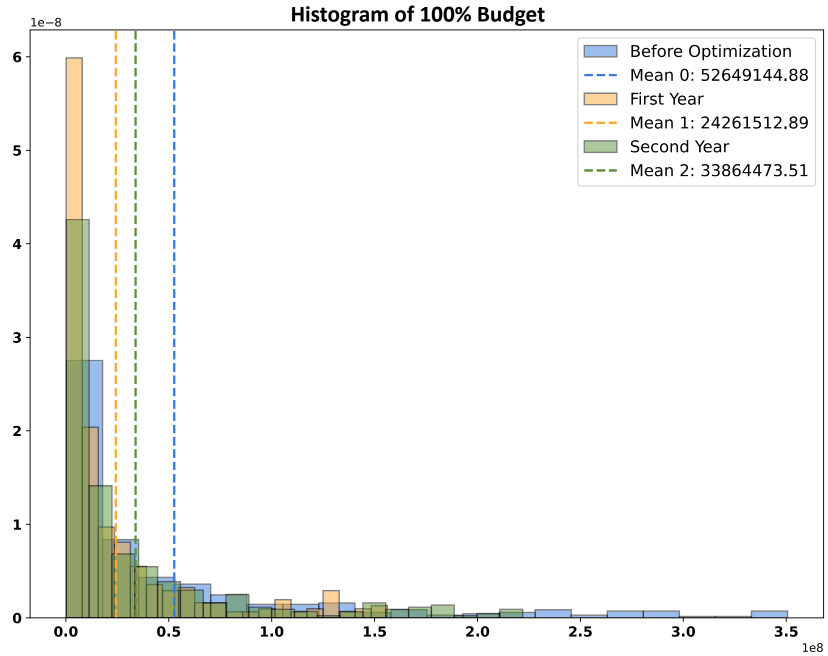

Figure 5: Histogram of Shipping Costs for 100% of the Total Budget (Density)

4.2 Two-Year Decision Making and Inflation Ratio Analysis

In this part of the analysis, we focus on the third model, which expands on the new model by introducing explicit decision-making at the beginning of the second year after observing first-year shoaling effects.

We introduced an inflation ratio to simulate increased costs for maintenance activities undertaken in the second year. The budget constraint was adjusted accordingly, ensuring second-year dredging and lock maintenance activities reflect higher real-world costs. Our results show that even with an inflation ratio as high as 1.5 (reflecting a 50% increase in second-year costs), significant second-year maintenance actions still proved beneficial in all scenarios. Table 2 shows the sensitivity analysis over budget and inflation ratio.

Table 2: Objective function values of different Inflation Ratio and Budget scenarios for second model

Budget \ Inflation Ratio	1	1.05	1.1	1.15	1.2	1.25	1.3	1.35	1.4	1.45	1.5
10%	4059297661	4033171960	3987891787	4048057383	4072964118	3985059851	4025468989	4069307258	3990428806	3962341627	4156147869
20%	2519731749	2806978573	2722791407	2715063848	2578723662	2513903031	2843402480	2542396317	2562020718	2565026460	2566003843
30%	1819656904	1565108913	1655245750	1783047866	1621353650	1748940068	1907742019	1695924372	2835546144	1672084521	1660714859
40%	1088050021	1056969355	1049642210	1111332400	1177079605	1224992879	1095104144	1076726055	1064158375	1235579849	1203133826
50%	779572638	884532071	784578086	858131769	857034392	834054112	816751586	822648181	770358517	924973328	832292665
60%	673793713	670768286	678228343	795339356	778771497	667425359	662127814	829272340	714189842	723856410	765804696
70%	589855783	593598945	598217517	596996405	627190638	617903645	603983809	617212242	613184061	642726258	614902116
80%	535154840	535625413	538412505	548392003	543238114	569153602	557487474	563851210	612976532	562916116	648432799
90%	517018676	501747642	501016007	546128016	539720671	510040163	518288850	514132103	511562243	525268891	527866745
100%	468259903	478258158	471563680	490437587	479108934	484342829	483850541	491700687	489416007	492454011	492043202

Reducing the inflation ratio closer to realistic lower bounds (e.g., 1.05) further increased the attractiveness and implementation of second-year maintenance activities, demonstrating the sensitivity and effectiveness of the expanded model. Table 3 presents the improvement in the objective function (in percentage), reflecting a reduction due to the minimization nature of the problem. In nearly all scenarios, the two-year decision-making model (third model) demonstrates a significant improvement in the objective function compared to the one-year decision-making model (second model).

This reduction highlights the benefits of incorporating a longer planning horizon, leading to more cost-effective dredging investment decisions and the potential for dynamic, multi-year maintenance strategies to considerably improve infrastructure management efficiency under variable economic conditions. It is important to note that each scenario required over 15 hours to reach a solution, making full optimization computationally impractical within a reasonable timeframe. To address this, a time limit was imposed on the solver, ensuring feasible run times while still achieving near-optimal solutions. As a result, the reported outcomes closely approximate the optimal solutions but do not necessarily represent the absolute optimum. This constraint also explains the observed inconsistencies between the results of different scenarios, as some solutions may have terminated before fully converging.

Table 3: Amount of improvement of third model compared to second model for different Inflation Ratio and Budget scenarios

Budget \ Inflation Ratio	1	1.05	1.1	1.15	1.2	1.25	1.3	1.35	1.4	1.45	1.5
10%	0.56	-0.09	-1.21	0.28	0.90	-1.28	-0.28	0.81	-1.15	-1.84	2.96
20%	-7.09	3.50	0.39	0.11	-4.92	-7.31	4.84	-6.26	-5.53	-5.42	-5.39
30%	-34.59	-43.74	-40.50	-35.91	-41.72	-37.14	-31.43	-39.04	1.92	-39.90	-40.31
40%	0.90	-1.98	-2.66	3.06	9.16	13.60	1.56	-0.15	-1.31	14.58	11.58
50%	-8.95	3.31	-8.36	0.23	0.10	-2.58	-4.60	-3.92	-10.02	8.04	-2.79
60%	-12.14	-12.54	-11.57	3.70	1.54	-12.97	-13.66	8.13	-6.88	-5.62	-0.15
70%	-17.19	-16.67	-16.02	-16.19	-11.95	-13.25	-15.21	-13.35	-13.92	-9.77	-13.68
80%	-22.78	-22.71	-22.31	-20.87	-21.61	-17.87	-19.55	-18.64	-11.55	-18.77	-6.43
90%	-21.23	-23.56	-23.67	-16.80	-17.77	-22.29	-21.04	-21.67	-22.06	-19.97	-19.58
100%	-26.66	-25.09	-26.14	-23.19	-24.96	-24.14	-24.22	-22.99	-23.35	-22.87	-22.93

5 Recommendations and Conclusions

This study aimed to optimize inland waterway maintenance operations by developing and comparing different modeling approaches for dredging project selection. Given the random shoaling, three models were examined to evaluate their effectiveness in improving maintenance strategies. The first model (old model) served as a baseline for this study and was developed prior to the other two models. The second model (new model) addressed one of the key limitations of the first model by incorporating the initial depth of each segment into the decision-making process. The third model, referred to as the extended model, addressed another critical limitation by shifting from a single-year to a multi-year decision-making framework, allowing for sequential decisions at each stage of the planning horizon. The models progressively increased the temporal scope and structural accuracy of the decision-making framework, allowing for more informed and adaptive budget allocation over time.

The first model provided a structured framework for scheduling and budgeting dredging operations considering random shoaling. However, a limitation was that it did not account for the initial depth of the waterways causing project optimization not to be based on the actual draft. As a result, dredging budget was not spent most effectively, and the model failed to allocate resources in the most strategic manner.

The second model incorporates initial depth as a critical factor to be able to measure resulting deeper draft from dredging on river segments, therefore, is able to measure new shipping capacities. The model demonstrated significant cost reductions compared to the first approach. The results indicated that considering initial depth allowed for more precise dredging schedules, reducing unnecessary maintenance expenses on some river segments while ensuring navigability. This model marked a substantial improvement over the first one, providing a more effective resource allocation. However, the second model still operated within a one period of time horizon and did not fully account for interdependencies between maintenance decision over multiple time periods.

The third model introduced a multi-period optimization strategy, further refining the decision-making process. This model not only accounted for initial depth but also allowed for dynamic budget reallocation and better long-term forecasting. The findings showed that the improvements achieved by this model were not marginal but significant, demonstrating that a more comprehensive, adaptive approach to maintenance planning leads to substantial efficiency gains. Compared to the second model, the third model offered enhanced cost savings, better scheduling accuracy, and a more effective long-term maintenance strategy.

Given the effectiveness of the third model, one of the most important takeaways from this study is the potential benefit of extending the forecasting horizon beyond the two-year period used in the analysis. Since we have established that this model provides significant improvements over the previous counterparts, future studies should focus on applying it to a longer horizon, such as 10 or even 20 years. Additionally, while this study used a deterministic approach to shoaling for simplicity, primarily to assess the significance of the model's improvements, an approximate way for the stochastic shoaling, the next step should involve solving the problem under stochastic conditions and through an iterative, dynamic process. This would better reflect the real-world uncertainties in shoaling patterns, budget fluctuations, and system conditions.

Additionally, this study highlights the potential of integrating advanced data analytics and machine learning techniques to enhance predictive maintenance capabilities. Real-time data collection and AI-driven decision-support systems could further improve adaptability and efficiency, ensuring that maintenance efforts remain cost-effective.

Our next step is to optimize for long-term, dynamic strategies that still considers stochastic shoaling of inland waterway networks.

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