Improved Waterway Network Maintenance Strategies via Genetic Algorithms

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ABSTRACT

Tasked with operations and maintenance of the navigable waterways throughout the nation, the U.S. Army Corps of Engineers must ensure sufficient depths in the ports and channels to allow commercial shipping vessels to move throughout the marine transportation network efficiently. Without regular maintenance dredging, the waterways experience sedimentation and resulting reductions in navigable depths, forcing vessels to travel at shallower depths by carrying less cargo, thereby increasing overall shipping costs. Since maintenance dredging funds are not available to fully maintain every federal navigation project to authorized dimensions, the Corps must determine the optimal distribution of funds across the ports and waterways to ensure minimum disruptions to shipping and maximum economic benefits nationally. To address this need, in this study detailed tonnage data from the Corps’ Waterborne Commerce Statistics Center for both deep and shallow-draft cargo are used along with representative shoaling rates and associated annual maintenance dredging costs for a slate of port areas around the country. A genetic algorithm (GA) is employed in pursuit of improved cost-effectiveness for annual maintenance dredging conducted across a large waterway network over a 20-year maintenance horizon, with total supported system tonnage used as the objective function quantity. The multi-year simulations are conducted for constrained budget scenarios in 10% increments for hundreds of port areas nationally. Comparisons with a project-based heuristic are made to gage the validity of the GA output.
1.0 INTRODUCTION

The U.S. Army Corps of Engineers maintains hundreds of federal navigation projects in deep-draft coastal ports and inland rivers and waterways throughout the nation. Hundreds of millions of dollars are invested annually on dredging and other waterway maintenance activities to ensure that channels and ports are kept at dimensions suitable for cost-effective, safe, and reliable commercial shipping [18]. Constraints on outlays from the Harbor Maintenance Trust Fund (HMTF) over several decades have resulted in a maintenance backlog of dredging projects [19], and the Corps has been forced to make difficult decisions concerning which navigation projects are to be given priority for limited funding [20].

In this research effort, the system-level effects of shoaling and subsequent dredging at individual navigation projects on the overall shipping network are modeled as part of an optimization formulation. Natural sedimentation or shoaling occurs in navigation channels as material is deposited by tidal, longshore, and/or riverine currents, thereby decreasing the channel depths (and widths) at which commercial vessels can safely navigate. Historic origin-destination tonnage data from the Corps’ Waterborne Commerce Statistics Center (WCSC) is used to obtain detailed information concerning how much cargo transits through a particular navigation project in a typical year. The data also describes the levels of tonnage carried at 1-ft vessel draft increments, enabling an objective measure of the tonnage that will be disrupted if any one location experiences shoaling to a specified depth. The fact that the WCSC tonnage data includes origins and destinations and associated routes allows for interdependencies across navigation projects to also be tracked. Historic Corps dredging budget data is used to develop estimates of dredging costs required to restore up to 4 ft of navigable depth within a single budget year at the navigation projects considered in this model. The intent is to find the optimal set of ports and channels to dredge over multiple 1-year budget cycles, subject to an overall fixed budget constraint in order to maximize the tonnage that can pass through the system in a given year.

1.1 Model Discussion

As mentioned above, it is important to note that the system in question is an interconnected transportation network of ports and waterways. The WCSC data not only describes the tonnage amounts that are loaded and unloaded at the various ports at particular drafts (and by inference channel depths), but also the connecting waterways that must be traversed by the shipments while en route. The implication is that these connecting channels must also be maintained to sufficient depths for transportation efficiency gains from maintenance dredging to be fully realized. The detailed WCSC origin-destination tonnage data and associated routes makes it possible to ensure that within the model, shoaling at any one
navigation project disrupts the tonnage passing at the corresponding vessel draft ranges, thereby impacting all the other projects that send, receive or otherwise handle the cargo. Similarly, only dredging one point in the system may not have any discernible impact on the overall network efficiency due to other locations not having equivalent depths. Within the model, this is handled by assuming that vessels pass through their entire route at the shallowest depth along the route, regardless of what greater depths may actually be available in the channels and ports along the way.

The maintenance dredging cost data is obtained by averaging historical Operations and Maintenance (O&M) budget amounts requested at each federal navigation project under consideration. The mobilization costs for dredge equipment at a particular project are assumed based on a fixed percentage of the overall funding levels requested for that project in a typical year. This full requested funding amount is assumed to correspond to the capability to restore up to four feet of navigable depth at the project. Smaller increments of restored project depth are then calculated according to Eq. 1:

\[ n\text{-ft restored Project Dredging Cost} = a \times Budget + b \times x^n \]  

where

- \( a \) = Fixed mobilization cost percentage
- \( Budget \) = full funding amount needed to restore 4-ft of depth
- \( b \) = Depth Coefficient = \((1 - a) \times Budget/4^n\)
- \( n \) = Power of Depth (degree of nonlinearity in depth-cost curve)
- \( x \) = Number of feet of restored depth

For the simulations conducted in this study, the mobilization/demobilization (mob/demob) costs are set to be a fraction of the overall cost of restoring 4-ft of depth, but these costs are fixed at that same rate for all other dredge-to depths as well. These costs represent the base rate to move all the equipment to the area and then remove said equipment afterwards, regardless of the amount of material actually removed during dredging. In the examples considered, mob/demob costs are normally distributed around 20% of the total 4-ft dredging depth cost with a 5% standard deviation. Here a minimum mob/demob percentage of 6.5%, a maximum of 31.4% and an average of 20.0% was used for the simulated budget years. Utilizing mob/demob costs emphasizes the oftentimes large fixed costs of moving equipment to the dredging site. It is anticipated that this dynamic will
result in dredging plans that call for less-frequent but deeper dredging rather than frequent
dredging of a small amount of material at projects with relatively high mob/demob costs.
The Power of Depth term controls the nonlinearity of increasing dredging costs as target
depths increase. If \( n = 1 \), then these costs increase linearly with depth. For the model
described in this paper, \( n = 2 \).

2 AN MIP FORMULATION

Previous iterations of this research were posed as a mixed integer problem (MIP) [4, 6].
This complimentary effort builds upon that work to include random shoaling processes, a
range of restored navigable depths, multi-year simulations, and variable mob/demob costs
in the model. However, the MIP formulation is still insightful as a model. For the single
year, single dredging depth model:

\[
\begin{align*}
\text{max} & \sum_i \sum_{j<i} b_{ij} x_{ij} & \text{s.t.} & \\
& x_{ij} \leq d_k & \forall i, j : i < j \text{ and } k \in S(i, j) & (2b) \\
& \sum_k d_k \leq x_{ij} + |S(i, j)| - 1 & \forall i, j : i < j \text{ and } k \in S(i, j) & (2c) \\
& \sum_i d_i c_i \leq B & \forall i, j : i < j & (2d) \\
& d \text{ binary} & \forall i; & (2e) \\
& x_{ij} \geq 0 & \forall i, j. & (2f)
\end{align*}
\]

In which,

\( x_{ij} \) \quad 1 \text{ when } i, j, \text{ and all intermediate ports are dredged.} \\
\quad 0 \text{ otherwise}

\( d_i \) \quad \text{Binary Decision Variable. 1 to dredge, 0 otherwise}

\( b_{ij} \) \quad \text{Increase in capacity by dredging } i, j \text{ and intermediate ports}

\( c_i \) \quad \text{Cost to dredge port } i

\( B \) \quad \text{Total Budget available}

\( S(i, j) \) \quad \text{Set of all projects necessary to receive benefit } b_{ij}

The MIP formulation dictates that the objective is to maximize the total cargo transiting the
system (2a). An increase in tonnage is only seen if the entire route is dredged (2b, 2c).
There is an upper bound cost constraint, so the cost of dredging the slate of chosen projects must be less than this constraint (2d). Partial dredging is not allowed in this earlier formulation, so either full dredging is conducted or no dredging is conducted at each location (2e). Constraint (2f) also indicates whether all projects along an origin-destination route have been fully dredged or not, with partial dredging yielding no incremental benefit.

2.1 Expansions on the MIP Formulation

This research expands on this previous work with several modifications to the model:

2.1.1 Multiple Traversal Depths:

The first iteration of the model assumed two states for each project, dredged or un-dredged. Therefore, only two tonnage amounts were enumerated at each location. The model has since been expanded to fourteen (14) possible depths at each location (0-13 feet of shoaling). Per the historic WCSC data, some projects may not have significant levels of tonnage at the very deepest depths, so dredging to these levels at those locations might not be cost-effective when compared to all other projects in need of maintenance dredging. However, just as in the MIP formulation, the benefit for the entire route is only realized at the shallowest depth in the path ($S(i, j)$).

2.1.2 Multiple Dredging Depths:

The original research focused on a binary “dredge or no-dredge” decision at each location. This research allows dredging decisions in a single budget year to restore as much as four (4) feet of navigable depth or not to dredge at all for each project considered in the model.

2.1.3 Multi-Year Simulation:

This research focuses on not only finding efficient dredging plans for a single budget year, but also how the dredging decisions evolve over several years (in this case, twenty years) as high-performing project achieve full maintained depths and less efficient projects shoal in over time. In addition to identifying the cost-effective and poor-performing projects, the goal is to understand the dredging cycles that will emerge over the course of the 20-year simulation in which navigation projects are dredged, allowed to shoal in, and then dredged again. The starting point for the next year in the simulation is the end state of the current year — including any shoaling or dredging decisions that were executed within that year.

2.1.4 Variable Shoaling Rates:

To create a realistic multi-year model of channel shoaling and subsequent dredging, the model employs random year-to-year shoaling rates, with the underlying probabilities
driven by the most recent dredging event and present depth of the project. In general, deep-draft channels that have been dredged recently will tend to shoal in more readily than will locations that are maintained at shallower depths or that have not been dredged in several years. The shoaling rate at each project location is probabilistically determined at the start of the year based on the previous year end-state (channel depth and previous year dredging decision). Any dredging that subsequently occurs also has to remove the sediment that is determined to shoal in later in that same budget year. It is possible for dredging decisions to actually result in a shallower project depth due to shoaling rates that may be greater (in terms of reduced navigable depths) than the depth increments restored by dredging. Since the model only considers dredging to occur at up to four feet of restored depth per year, shoaling rates are capped at three feet per year to ensure that it is at least possible to continually improve the system from one year to the next given sufficient resources (i.e. dredge funding), even for high-shoaling projects.

2.1.5 Variable Mob/Demob Costs:

This fixed portion of the dredging cost is a nontrivial factor in the decision making process. If mob/demob costs constitute a very high percentage (say 50% or more) of the total dredging cost to restore one foot of navigable depth to a project, then decision makers would seemingly choose to only dredge that project on an infrequent basis, albeit to a greater extent than they might otherwise during years when dredging does take place. If, however, the mob/demob costs are on the order of only 5 – 10% of the total cost, then year-over-year dredging with perhaps only a foot or two restored at a time might well be a cost-effective maintenance strategy. For this study, the mob/demob factor is fixed at the onset of the process for each dredging project and does not change throughout the 20-year simulation.

3 FUNCTION FORMULATION

The following will describe how the model presented in Section 2 above can be solved using a Genetic Algorithm (GA). The settings unique to the GA will be discussed later in Section 3.3.2.

3.1 Data Storage

A primary challenge for solving this system is organizing and accessing the data in a fashion that is minimally computationally intensive. The problem is formulated as a linear matrix equation, utilizing Python [8, 5] and NumPy’s [11] indexing modules to quickly access data.
3.1.1 Shipping Routes

The data representing each route is read into a sparse matrix, and each row of the matrix is a shipping route between an origin and destination port, and each column represents a port or waterway segment in the system ($n_{routes} \times n_{ports}$ in dimension). If the port or waterway noted by the column is part of the shipping route, a 1 is placed in the matrix; otherwise the entry is left 0 for sparsity. For the results in this paper, $n_{ports} = 208$ ports and $n_{routes} = 3,568$ routes.

3.1.2 Tonnage and Cost Data

The tonnage amounts in the WCSC data associated with each 1-ft increment of available channel depth (and by extension, the disruptions incurred by various shoaling amounts) are stored in a dense matrix, each route using one row and the columns representing the tonnage transiting at that depth ($n_{routes} \times n_{depth}$). The costs are similarly stored, one row per project and each column represents a dredging option ($n_{ports} \times n_{dredgeOptions}$).

3.1.3 Dredging Decision

The decision variable (the “chromosome” for the GA) is a vector with $n_{ports}$ elements representing the dredging decision at each port [$0, \ldots, n_{dredgeOptions}$]. As an example, the following would represent the decision to dredge depths of 3, 4, 1, and 0 feet for the first four ports in the system and 2 for the last port in the system: [3, 4, 1, 0, …, 2]. This chromosome is converted to a sparse matrix by the code with a unit entry in the column corresponding to the dredging decision and zeros elsewhere. For the above example, the conversion would result in:

[$[0,0,0,1,0] [0,0,0,1] [0,1,0,0,0] [1,0,0,0,0] \ldots [0,0,1,0,0]]$. This matrix can be multiplied by the route matrix in order to provide a count of dredging decisions along each route.

3.1.4 Present Depth

The present depth of the system is stored in a vector that has $n_{ports}$ elements, each representing the depth at the respective port. This is adjusted at each time step throughout the 20-year simulation according to the dredging decision made and the subsequent shoaling.

3.2 Evaluate the Function

Using this data storage technique described above, the data can be efficiently queried in
order to obtain the information required to evaluate the dredging options provided by the
GA.

3.2.1 Cost Evaluation

The first step is to evaluate whether the proposed dredging schedule violates the overall
budget constraint. The cost at each port given the dredging decision is extracted and the
resulting vector is summed to obtain the total cost of the dredging plan. This total is
subtracted from the maximum budget amount, and if the total dredging cost exceeds the
budget constraint a negative number will result. In this way, vital information is provided
to the GA, thereby taking it down a path away from infeasible options to those that do not
violate the cost constraint.

3.2.2 Compute Depth

If the dredging option does not violate the overall cost constraint, then the depth vector is
modified by the entries in the dredging vector to obtain the new depths for all projects at
the end of the budget year.

3.2.3 Compute Tonnage

To compute the tonnage passing through the system given a dredging plan (i.e. a slate of
projects to be dredged along with the dredge-to depth at each), the post-dredging depths
are converted to a matrix $n_{ports} \times n_{depths}$, with a 1 in the column of appropriate depth for
each port and a 0 otherwise. Then a sparse-dense matrix multiply is conducted with the
route/tonnage matrix and this newly-formed depth matrix. This yields the number of ports
at each depth for each route ($paths = n_{routes} \times n_{depths}$ in size).

The shallowest point for the route is given by the first nonzero on each row. Here, $argmax$
utility within NumPy is used and an efficient $where$ command to return a list representing
the index of the first nonzero on each row: $argmax(paths > 0, axis = 1)$, where the paths
matrix is the count of depths occurring along each route. It is important to note that the
“Shallowest Point” calculating will be called hundreds of thousands of times over the
course of the GA implementation, therefore care must be taken that it is performed as
efficiently as possible. Initial formulations of the algorithm used loops or Python list
comprehensions to find the shallow point, but these methodologies increased the
computational effort by several orders of magnitude. Once the shallow point along each
route is found, it is straightforward to index into the tonnage array at the shallowest point
to find the tonnage that is able to pass through the system with the proposed dredging
schedule. This amount is summed and the maximum value is sought by the GA.
3.3 Optimizing the Decision Algorithm

3.3.1 Genetic Algorithms

We chose to solve for the optimal dredging locations using a Genetic Algorithm (GA) as coded in Python (using PyEvolve [14]). Genetic Algorithms were discovered over the course of Kenneth De Jong's PhD research with John Holland [7, 8]. Genetic Algorithms (GA) are used in a variety of global optimization problems, including parameter estimation in groundwater problems [6], networks [3, 1], and transit design [5]. As shown by More [12], Yeh [17], Deb [4], and discussed in [2, 15], GA's perform very well in benchmarking tests against other optimization techniques. Genetic Algorithms use the genetic operators of crossover and mutation to modify the components (genes) of the solution (chromosome). The crossover process selects part of one chromosome and pairs it with part of another to create a unique third chromosome. The example from De Jong's thesis is in Figure 1. PyEvolve uses a single point crossover similar to the image.

![Figure 1 – Crossover process example from DeJong’s thesis [8]](image)

Mutation, on the other hand, modifies the new chromosome with information not present in either parent. Both settings are tunable in the Pyevolve algorithm. For this study, many Crossover and Mutation rates have been tested to determine their effects on the algorithm. The GAs are initialized with two random seeds and runs are executed independently. Crossover rates are chosen at 0.05 spaced increments along the [0.3, 1] interval, while mutation rates were selected from [0.01, 0.05]. Having run the GAs at these fixed values of the crossover rates and mutation rates (as shown in Figure 2), the maximum raw values are captured upon completion of generation 2000. The matrixed results shown in Figure 2 reflect the arithmetic average of these runs for each pair of crossover rate and mutation rate, while the color gradient emphasizes the range from most to least computationally efficient.

A third key element of GA performance is the population size of each iteration; that is, how many various chromosomes should be examined before settling on a best fit. The effects of population size on convergence are not explicitly tested for here, but the PyEvolve default size of 80 for the population yields adequate convergence given sufficient iterations. This number is also in line with recommendations from other applications of genetic algorithms [21, 22].
Finally, varying numbers of iterations have been tested to determine at what point the GA has ceased to improve the solution quality. Figure 3 demonstrates that the solution has ceased to improve well before the cutoff of 2000 iterations has been reached. In this figure, the green bars represent the maximum and minimum value achieved at each iteration. The blue line is the average value for the iteration. The “Raw Score” is the tonnage that passes through the system with the given dredging scheme. The lack of improvement for the maximum value after iteration 1000 indicates the GA has settled on a local maximum.

Figure 2 - Effects of Crossover and Mutation Rates on Solution Quality

Figure 3 - Iteration History for Genetic Algorithm
3.3.2 GA Implementation Details

The following discussion concerns the specific settings and implications for the Genetic Algorithm. This discussion is not necessary to understand the broader algorithm and its implementation towards the dredging decision problem, but it may be of interest to those seeking to replicate the results discussed subsequently. Also, it should be noted that there is a broad range of options to choose from for each setting. Since the intent of the research is to explore implications for maintenance dredging decisions across a large portfolio of navigation projects, most settings are selected as typical or default for GA use.

The GA is initialized at each time step during the 20-year simulation with a random choice from the allele (where the allele is the number of dredging options [0, 1, 2, 3, 4]). So each entry in the decision vector (chromosome) is populated with a random number [0…4]. The mutations are performed by randomly selecting a number of genes in the chromosome and then inserting a new value from the allele in that location. The number of genes to replace is determined by the mutation rate times the size of the chromosome. For the mutation rate of 0.01 and list of 207 ports, it is expected that two entries in the chromosome are randomly replaced during each iteration.

Once the population has been compiled, a Roulette Wheel selection method is used to determine the “parents” for the next generation. To achieve this, each chromosome gets entry into a random table based on its fitness function (in this case, the tonnage that passes through the system under the dredging scheme). Chromosomes with better fitness functions will have larger entries in the table. The chromosomes are listed in order and then a random number is selected in the range of the sum of all the fitness functions. The chromosome corresponding to that point in the table is returned as a parent for the next generation. This method does not necessarily return the “best” chromosome for that generation for a parent, but will tend to return more fit chromosomes as the evolution progresses.

To permit negative fitness function scores (indicating infeasible dredging choices resulting from exceeding the budget), the fitness function is scaled using Sigma Truncation. This allows the GA to consider the fitness of a generation that may vary by orders of magnitude by comparing the standard deviation from the mean for each member of the population.

3.3.3 Timings

In order to conduct sensitivity analysis of how the dredging schemes identified by the GA change with allowable budgets, the budget constraint is increased in 10% increments (10%
. . . 100%) in parallel. The simulations are repeated for 20 years of shoaling/dredging
cycles for each budget scenario. On average, each year requires 430 sec to complete, or just
over 7 minutes. This compares very favorably to solving the MIP formulation from [9].

4 DISCUSSION OF RESULTS

The output from the GA provides the depth at which to dredge each navigation project in
the waterway system each year. In these results, the depth to dredge ranges from 0-4 feet
and there are 20 years of simulated time. From the dredging decision indicated by the GA
output, the new, post-shoaling depth of the location can be discerned and the total tonnage
that can pass through the system given this range of maintained depths across all projects
can be determined. These are powerful results in that they can be used both to track
individual projects in terms of lifecycle maintenance outlays under a range of overall
budget constraint scenarios, but also at the system-level to see how these same overall
budget constraints impact the efficiency of the entire portfolio of projects. Such a
capability has significant implications for the Corps of Engineers as it attempts to achieve
objective, transparent stewardship of taxpayer dollars during projected lean budget cycles.

The GA results for the dredging/shoaling decision model presented here reveal some
interesting trends and findings that will contribute to a greater understanding of multi-year
dredging cycles and the impact of budgetary constraints on port system lifecycle
functionality. Fig. 4 shows the total system tonnage restored by dredging (of previously
unavailable channel depths) for each year in the 20-year simulation for four different
budget constraints. For these examples, 100% represents the funding amount required each
year to dredge each location and restore four feet of navigable depth. When the total
budget represents only 10% of all requested dredging funds, the overall restored system
tonnage increases slowly through the years, and only achieves about 40% of the potential
maximum tonnage total (just over 100M tons in this example) even after 20 years of
efficient dredging decision slates, per the GA results. The 30% and 50% budget scenarios
show significant increases in supported tonnage, but it is also interesting to note that they
also“level out” after about 12 years and never appear to go much higher than about 75%
and 95% of the total system tonnage. This seems to indicate that the rules governing
shoaling rates in the model result in dredging demands across the portfolio of projects that
balance out the funds available. The overall system of channels is never able to achieve
total system tonnage restored via fully-maintained channels. Finally, at the 70% budget
request scenario, the restored system tonnage is seen to max out in Year 8 of the
simulation, after which the entire portfolio of channels is fully maintained. These findings
are interesting because they provide a framework by which year-over-year improvements
in overall navigation system performance may be tracked, and multi-year maintenance
dredging work plans and schedules may be developed that gradually improve the overall
levels of service even in the face of constrained annual budgets.

Figure 4 – Restored system tonnage over 20-year simulation for varying budget constraints

To provide a measure of validity to the optimal dredging plans produced by the GA, a
simple value-density heuristic is introduced to get an idea of which projects are most
efficient to maintain in terms of the rates of annual tonnage throughput and relative costs to
dredge. The total tonnage transiting through each project within 7 ft of the deepest project
depth was divided by the corresponding total annual dredging budget request for each
project. The resulting ratio provides a simple basis in terms of average expenditures per
 ton of cargo (using the 7 deepest feet, that is, the range most directly dependent on year-
over-year maintenance dredging). The projects are then sorted high-to-low using this
simple heuristic. Figure 5 shows the resulting slate of rank-ordered projects, with each row
representing a dredging project and each column representing the progression across the
20 budget years simulated. A color coding scheme is applied to help show which projects
are being fully maintained (green) and which are being allowed to consistently shoal in
(red) under the 60% budget scenario. As expected, those projects near the top end of this
listing, those with the highest tonnage/$-expended ratios, tend to be preferred by the GA
for full maintenance dredging. Those with lower ratios via this tonnage/$-expended
heuristic, those near the bottom of the table, are consistently allowed to shoal in. It is also interesting to note that many of the projects that are allowed to shoal in are in general geographic proximity to one another, indicating that they likely share much of the same cargo. The GA would therefore appear to be screening out groups of less-efficient (per the heuristic) projects whose performance is highly interdependent owing to their shared cargo, in the interest of moving scarce dredging funds to other projects where more overall benefits can be realized. The relative handful of orange and red projects near the top of Fig. 5, as well as the pockets of green near the bottom, likely are due to the shared tonnage with other projects. Less-efficient projects may be benefiting in some cases from sharing cargo with more efficient projects, and vice versa. Also, several of the projects near the bottom of Fig. 5 are very small in terms of commercial tonnage, yet also are relatively inexpensive to maintain. Therefore the GA essentially sees little penalty to including these projects (perhaps no other projects will fit within the budget ceiling), even if the additional tonnage is negligible.

From the perspective of individual projects, the GA output shows the progression of channel conditions through the budget years, as depths are gradually restored for more efficient projects while others are allowed to shoal in over time, depending on the budget ceiling. Figure 6 shows the 20-year project condition histories of four representative dredging projects considered in the model under the 60% budget scenario. The Sabine-Neches Waterway and the Hudson River Channel, both high-tonnage projects and both in the top 50% of projects in terms of the value-density heuristic described above, are restored to full project depth over the course of about 6 budget years, while Nome, Alaska is largely passed over for maintenance funds until about year 15. Nome is ranked near the bottom of all projects in the model according to the value-density heuristic, but it also has one of the lowest annual dredging costs, which might have made it easy for the GA to include it in the dredging slate of projects ahead of some others. Due to low levels of recorded tonnage and relatively expensive dredging costs per the budget histories, Bayou Teche, Louisiana is allowed to shoal in according to the GA.
Figure 5 – Visualization of optimal dredge plans for 60% budget scenario, with projects rank-ordered according to a simple value-density heuristic.
Figure 6 – Project maintenance histories at representative locations from GA with 60% budget scenario

5 SUMMARY AND CONCLUSIONS

This work presents the utilization of a genetic algorithm (GA) to solve a large annual maintenance dredging decision problem across a 20-year system lifecycle. The GA solution has demonstrated results that arrive at consistent, efficient dredging solutions with reasonable levels of computational effort. This work builds upon previous optimization formulations using mixed-integer methods applied to maintenance dredging project selection problems [9,11].

Year-over-year increases in the amounts of total restored system tonnage are observed for all budget scenarios tested, which might lead one to conclude that the multi-year GA approach is able to take advantage of a sequencing effect of dredging jobs across years in order to achieve more efficient solutions while still complying with yearly budgetary constraints. However, it should be noted that the model presented in this paper does not explicitly “look ahead” in order to find true lifecycle optimization maintenance plans. Rather, the GA search is only conducted at each 1-year increment of the simulation, with the best dredging maintenance plan found in one year setting the initial project conditions for the next year. Future work will focus on extending the number of years over which the GA searches in order to explore the implications of sequencing of maintenance dredging across years, with more dredging occurring at each location but with more time elapsing between dredging events. In addition this model will be applied towards sensitivity analysis to show how localized dredging unit costs as well as mobilization costs for dredge equipment contribute to optimal dredging cycles at navigation projects, and programmatic efficiency gains across the entire project portfolio.
6 REFERENCES


