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Supporting Secure and Resilient Inland Waterways: Phase Two
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Abstract

To mitigate inland waterway disruption impacts, we developed the cargo prioritization and terminal allocation problem (CPTAP) to minimize the total value loss of disrupted barge cargoes. CPTAP is formulated as a mathematical program, and problems of realistic size can be efficiently and effectively solved with a heuristic approach. The final solution identifies an accessible alternative terminal for each disrupted barge and the prioritized offload turn that each barge takes at its assigned terminal. Implementation of CPTAP results in reduced cargo value loss and response time when compared to a naïve minimize distance approach. This project extends our earlier work through CPTAP model enhancement by incorporating uncertainty impacts into the model and experimentation.

1. Project Description

Comprised of approximately 12,000 miles of navigable waterways, the U.S. inland waterway system is a commercially and strategically important transportation mode. It is especially critical for certain commodities (e.g., agricultural and coal & petroleum) and geographical regions. Unexpected disruptions to the system due to natural disasters, vessel accidents, or terrorist attacks can cause non-navigable water levels or destroy major navigation infrastructures (e.g. bridges, locks and dams) resulting in closures of the inland waterway and consequent economic and societal impacts. We developed an optimization approach to the cargo prioritization and terminal allocation problem (CPTAP) to provide decision support for disruption response stakeholders in order to minimize the total value loss of cargo disruptions on the inland waterways. The details of the CPTAP formulation as well as a Genetic Algorithm heuristic to solve the model can be found in Tong and Nachtmann (2017). Uncertain features such as barge transportation speed on the river and expected cargo arrival dates were not included in initial formulation of CPTAP. In this project, we develop and employ a more realistic CPTAP model using Monte Carlo simulation which allows us to more realistically model inland waterway transportation impacts after disruption. The developed approach enhances current CPTAP decision support and improves pre-event planning by assessing the resiliency of the inland waterway transportation system to handle potentially disrupted cargo under uncertain conditions.

2. Literature Review

We examined two sets of relevant literature, both of which provide insights in exploring approaches to incorporate uncertain factors into CPTAP. Berth allocation problem (BAP) has similarity with the CPTAP, and we conducted a literature review on the deterministic BAP problem in our previous research (the majority of BAP literature solves deterministic BAP). The first set of literature we investigated in this research is the stochastic BAP (i.e., BAP with uncertain factors). For the second set of literature, we investigated the literature that focuses on port related simulation models. The first set of literature lays out the potential approaches of handling uncertainties for the CPTAP, and the latter set of literature emphasizes the approach we selected (Monte Carlo simulation) under an extensive context (port related).

2.1 BAP with Uncertainty

Xu et al. (2011) studied uncertain arrival time and handling time in the BAP. A special buffer time between the vessels assigned to the same berth was adopted as the decision variable to represent the vessel delays and handling time. These authors proposed a robust berth allocation problem (RBAP) model to obtain a balance between the service level and the baseline berth plan robustness. A hybrid heuristic algorithm that combines simulated annealing and branch-and-bound algorithm was developed to tackle the RBAP. Numerical experiments were conducted to show that the RBAP was solved effectively by the proposed heuristic. Zhen (2015) introduced two models to address the random operation time of the vessels in a tactical berth allocation problem - a stochastic programming model formulation with a parameter to represent deviation between the estimated and actual number of containers handled at the port, and a robust model formulation that can limit the worst-case outcome. Meta-heuristic was proposed to solve large size problems within a reasonable CPU time. Uncertain arrival time is the major concern in Budipriyanto et al.'s 2015 research article. These authors developed a conceptual model that encourages the collaboration between different terminal operators in sharing assets and jointly planning the berthing schedules. The objective of their conceptual model is to minimize the idleness of terminal facilities and resources and to improve the overall resource utilization at multiple terminals. Similar to Xu et al (2011), Liu et al. (2016) also took arrival time and operation time into consideration as the uncertain parameters in the BAP. These authors developed a mixed-integer and two-stage stochastic formulation, and the proactive handling way was used for the uncertainty. An adaptive differential evolution algorithm (ADE) was employed to solve the proposed problem and proved to be effective in solving BAP under uncertainty. Xi et al. (2017) again focused on the arrival times and operation times of the calling vessels. A discrete number of scenarios was used to represent the uncertainty. A bi-objective BAP with objective functions on economic performance and customer satisfaction was developed, and an adaptive grey wolf optimizer algorithm was adopted to solve the BAP. Based on their previous work in 2015, Budipriyanto et al. (2017) built a simulation model to investigate how the non-collaborative-response and collaborative-response between berth terminals affect port performance under uncertainty. Not surprisingly, the authors found that the collaborative approach leads to a shorter waiting time, operation time, and total ship turnaround time.

2.2 Simulation in Ports and Container Terminals

There is an extensive amount of literature on simulation models applied to port and container terminal operations. We selected five research papers that employ a simulation-optimization framework which relates to our research problem for review. Zeng and Yang (2008)'s research examined approaches to schedule the loading/unloading of containers at the container terminals. They first used optimization to find the solutions of the container sequence and then employed simulation (using Arena software) to evaluate the solutions generated by the optimization model. Numerical experiments justified the effectiveness of the integrated optimization-simulation method. The quay crane scheduling problem was investigated by Legato et al. (2008). They proposed an integer programming formulation for deterministic discharge-loading times and developed a simulation-based optimization method for uncertain discharge-loading times (exponential or hyper-exponentially distributed). Sacone and Siri (2009) developed a scheme of simulation-optimization integration for solving operational planning problems in seaport container terminals. Arena software was used to represent the dynamic behavior of the terminal, and the optimization model was used to obtain certain system parameters which were adopted as inputs for the simulation model. Legato et al. (2010) further investigated the discharge/loading process using a simulation-based optimization model. A simulated annealing procedure was developed to search for the crane schedules while a discrete-event simulation model was used to estimate parameters for the heuristic algorithm. The uncertainty due to the port congestion and an unfixed port operation time was considered by their simulation optimization model. Based on their prior research, Legato et al. (2014) applied the simulation optimization concept to the berth allocation problem (BAP), which was solved by a programming model at a tactical level and a simulation model at the operational level. Both beam search and simulated annealing were employed in the optimization framework, and Monte Carlo simulation was adopted to capture all sources of randomness at the operational level.

3. Methodological Approach

3.1 Discussion on Water Transport Time Uncertainty

In the CPTAP model, water transport time functions as one of the important parameters in the objective function and the value loss constraint. In our initial work, we assumed that water transport time is a fixed parameter once the barges are assigned to their terminals by using an average water transport speed of five miles per hour (mph), and therefore, all barges traveling on the inland waterway from their current location when the waterway is disrupted to the offloading terminal adopt the five mph speed assumption in CPTAP. The speed value was estimated by observing the movement of ninety-six barge tows on the studied river section – from Lock/Dam 14 to Lock/Dam 19 on the Mississippi River in September 2012. The simplification of the barge speed was necessary to formulate a deterministic nonlinear integer programming model and evaluate its effectiveness. However, we recognize that under real world conditions, barge speed is an uncertain parameter affected by a variety of factors. For example, barges may travel slower if it needs to pass through one or multiple locks on its way to the assigned terminal due to the waiting time and the processing time at the lock. Therefore, in this research, we are interested in expanding our CPTAP model of normal and disrupted inland waterway transportation with the ability to handle uncertain barge traveling speed. Our research team explored the U.S. Army Corps of Engineers Navigation Data Center and ran the lock queue report of the studied river section every fifteen minutes over a period of a few days. By stacking locks within the same river system and following the barge tow's movement across multiple locks, we were able to develop the distributions of the barge speed of different moving directions and under various waterway scenarios, as shown in Figure 1.

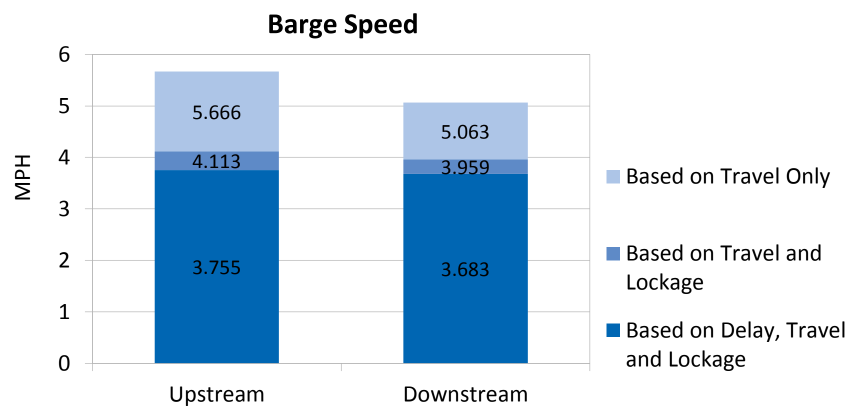


Figure 1. Barge Speed for Travelling Up/Down the Studied River Section

The three scenarios considered are as follows:

- Based on Travel Only: The disrupted barge tow will not move across any Lock/Dam on its way to the assigned terminal.
- Based on Travel and Lockage: The disrupted barge tow will move across at least one Lock/Dam on its way to the assigned terminal but there is no abnormal delay at the Lock/Dam.
- Based on Travel, Lockage and Delay: The disrupted barge tow will move across at least one Lock/Dam on its way to the assigned terminal and there is the abnormal delay at the Lock/Dam.

From Figure 1, we observe that the barge tow moves faster when going upriver in all three scenarios, and it is not difficult to anticipate a slower barge speed when the barge travels across the Lock/Dam with delays.

3.2 Discussion on Monte Carlo Simulation

To model the uncertain water transport speed in the CPTAP, simulation is an appropriate approach that meets our model requirements. There are over fifty different simulation languages, software, and simulators that have been used in port and terminal simulation modeling (Dragovic et al, 2016). We selected the Monte Carlo method, which is a simple but robust simulation concept that can be coded into our existing CPTAP Genetic Algorithm (GA) C++ programming code. The pseudocode of the GA with the Monte Carlo procedure is presented in Figure 2. Given the distributions of the speed values, we are able to generate different speeds under different scenarios for barges traveling on the inland waterway. Water transport time is developed based on the generated speed. We run the CPTAP model for each generated speed to get its Genetic Algorithm solutions and then summarize the overall Genetic Algorithm solutions.

Pseudocode CPTAP GA Approach with Monte Carlo Simulation Procedure

```
READ data of general information of terminal, barge and cargo
SET i to 0
FOR i is less than the number of the random scenarios that to be generated
    WHILE the generated speed not feasible
        Generate a new speed value
    ENDWHILE
ENDFOR
SET mc to 0
For mc is less than the number of the random scenarios that to be generated
    Revise water transport time based on the speed
    SET m to 1
    WHILE m < Iteration number
        Conduct Tournament selection to select two parents
        Conduct Crossover to produce two children
        Conduct Mutation on the two children
        Conduct Repair to produce two structurally feasible children
        CALL SolutionValue RETURNING objective function values of two children
        IF the child does not share the same objective function value with chromosomes in population
            IF the child performs better than the worst chromosome in the population
                Include the child into the population
            ENDIF
        ENDIF
        INCREMENT m
    ENDWHILE
ENDFOR
```

Figure 2. GA Approach with Monte Carlo Simulation Procedure Pseudocode

4. Results/Findings

We evaluated the optimization-simulation CPTAP model using the previously generated data instances used for testing the CPTAP GA-based heuristic. We provide a brief explanation on instance generation here and detailed information can be found in Tong and Nachtmann (2017). The instances are generated from the data collected on the 154-mile river section on the Mississippi River from Lock/Dam 14 to 19.

Barge location, cargo offload time, and land transport time are also modeled as uncertain parameters and generated according to Uniform distributions. Barge volume and terminal capacity are set as 1000 tons per barge and 5000 tons per commodity type respectively. The cargo value on each barge is calculated by multiplying the barge volume and its market unit price. Barge draft is estimated based on its probability density function developed from the draft data of vessel trips. For the value decreasing rate (VDR) parameter, hazardous cargo (all petroleum and 50% of the chemicals) is given the highest VDR (0.6 per ton per hour), nonhazardous chemicals and perishable products receive the second highest VDR (0.4 per ton per hour), crude materials and primary manufactured goods take the third place (0.3 per ton per hour), and the lowest VDR goes to the coal (0.1 per ton per hour). We evaluated the optimization-simulation CPTAP model using three types of instances – small, medium and large, which are defined based on the number of terminals and barges involved in the instances: small size instances include five terminals and nine barges, medium size instances have ten terminals and thirty barges, and large size instances include fifteen terminals and fifty barges.

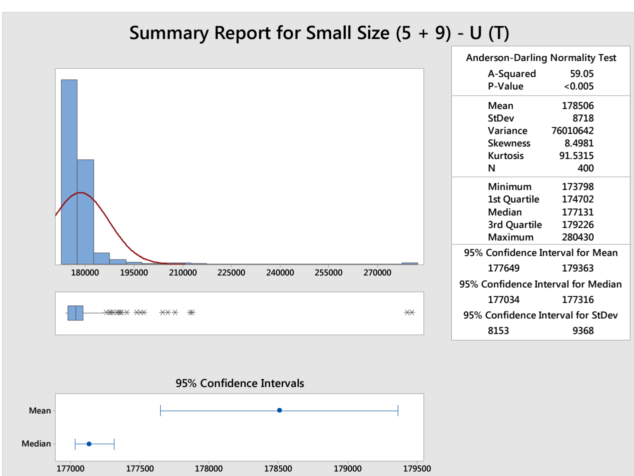
In terms of the data needed for the simulation procedure, we generate four hundred simulation iterations that can limit the CPU time within a reasonable limit for small and medium size instances. For large size instance, the simulation results cannot be obtained in forty-eight hours. Therefore, we use an alternative approach to generate and combine the results. Table 1 summarizes the normal distribution parameters for the barge speed used in this research. The related discussion was provided in Section 3.1.

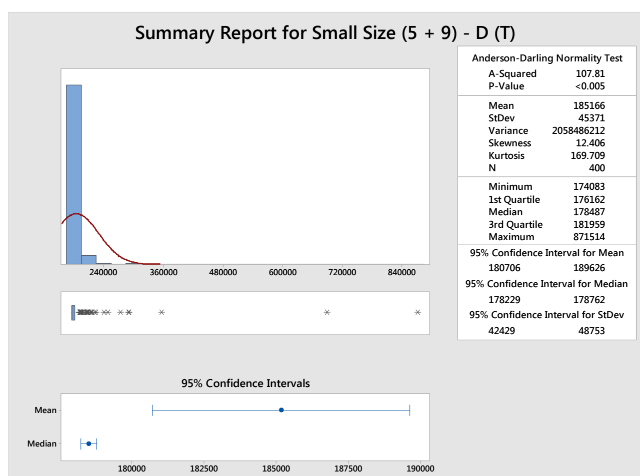
Table 1. Normal Distribution Parameters for Barge Speed

Scenarios for Barge Speed	Upstream mph		Downstream mph	
	Mean	StDev	Mean	StDev
No L/D Crossing (based on Travel)	5.666	18.42	5.063	6.332
L/D Crossing with No Delays (based on Travel and Lockage)	4.113	9.771	3.959	4.699
L/D Crossing with Delays (based on Travel, Lockage and Delay)	3.755	6.594	3.683	4.413

4.1 Small Size Instance Results

Figure 3 displays the optimization-simulation CPTAP results for a small size instance with the different river scenarios. We run the C++ programming code for CPTAP GA together with the Monte Carlo simulation for barges travelling up and down the river under three scenarios that affect the barge speed, resulting in six summary reports that are processed by Minitab. Based on these six reports, we observe that none of the simulation results follows a normal distribution and they are all positive (right) skewed, indicating majority of the simulation results center around the minimum (or best) optimization value with a few of outliers that represent very high total value loss. Looking at the 3rd Quartile values for all six reports, 75% of the simulation results are less than or equal to 3% to 4% increase of the minimum value loss, which shows that a significant amount of the four hundred simulation iterations produce results that are very close to the minimum total value loss.





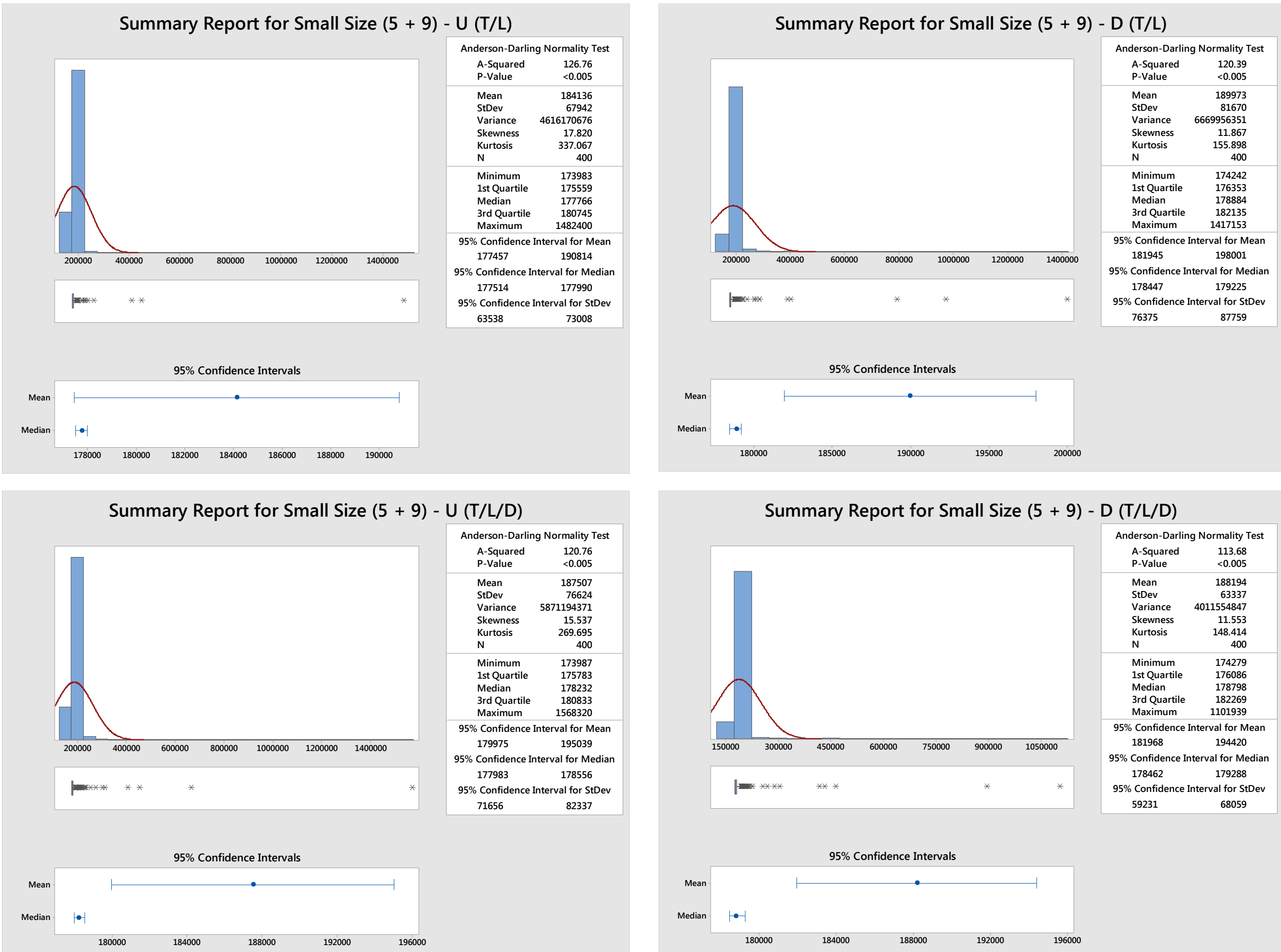


Figure 3. Small Size Instance Optimization-simulation Results

In addition to the general pattern for all six summary reports, we also observe some differences across the reports. Barges travelling downstream have a higher mean for their simulation results (185166, 189975, and 188194 respectively) compared to the ones going upstream (178506, 184136, and 187507 respectively). Other statistics such as “Minimum”, “1st Quartile”, “Median” and “3rd Quartile” all exhibit similar trends between upstream and downstream movements. It indicates that the downstream barge owners will suffer a comparatively higher value loss compared to the upstream barges when the waterway is disrupted. Table 2 displays the best simulation results for small size instance. The best solution that leads to the minimum simulation result is the same for all scenarios (it is the optimal solution). The CPU time is consistently between 484 and 488 seconds.

Table 2. Small Size Instance Simulation Results

Scenario	Minimum Simulation Result ($)	Best Solution	CPU Time (s)
Up (Travel)	173797.970	Terminal 1: 1 9 4 Terminal 2: 3 8 6 Terminal 3: 2 5 Terminal 4: 7	484.366
Up (Travel & L/D)	173982.677	Terminal 1: 1 9 4 Terminal 2: 3 8 6 Terminal 3: 2 5 Terminal 4: 7	484.668
Up (Travel & L/D & Delay)	173986.902	Terminal 1: 1 9 4 Terminal 2: 3 8 6 Terminal 3: 2 5 Terminal 4: 7	485.889
Down (Travel)	174082.520	Terminal 1: 1 9 4 Terminal 2: 3 8 6 Terminal 3: 2 5 Terminal 4: 7	485.880
Down (Travel & L/D)	174242.366	Terminal 1: 1 9 4 Terminal 2: 3 8 6 Terminal 3: 2 5 Terminal 4: 7	488.058
Down (Travel & L/D & Delay)	174279.029	Terminal 1: 1 9 4 Terminal 2: 3 8 6 Terminal 3: 2 5 Terminal 4: 7	485.901

4.2 Medium Size Instance Results

Figure 4 displays the optimization-simulation CPTAP results for a medium size instance with the different river scenarios. Based on the six reports for the medium size instance, again we observe that none of the simulation results follow a normal distribution and they are all positive (right) skewed, indicating majority of the simulation results center around the minimum (or best) optimization value with a few of outliers that represent very high total value loss. Looking at the 3rd Quartile values for all six reports, 75% of the simulation results are less than or equal to 8% to 11% increase of the minimum value loss, which shows that a significant amount of the four hundred simulation iterations produce results that are close to the smallest total value loss. However, due to the bigger search space of the medium size instance, it becomes more difficult to reach the minimum value loss. Similar to small size instance, a higher mean of the value loss is observed for barges moving downwards compared to moving upwards.

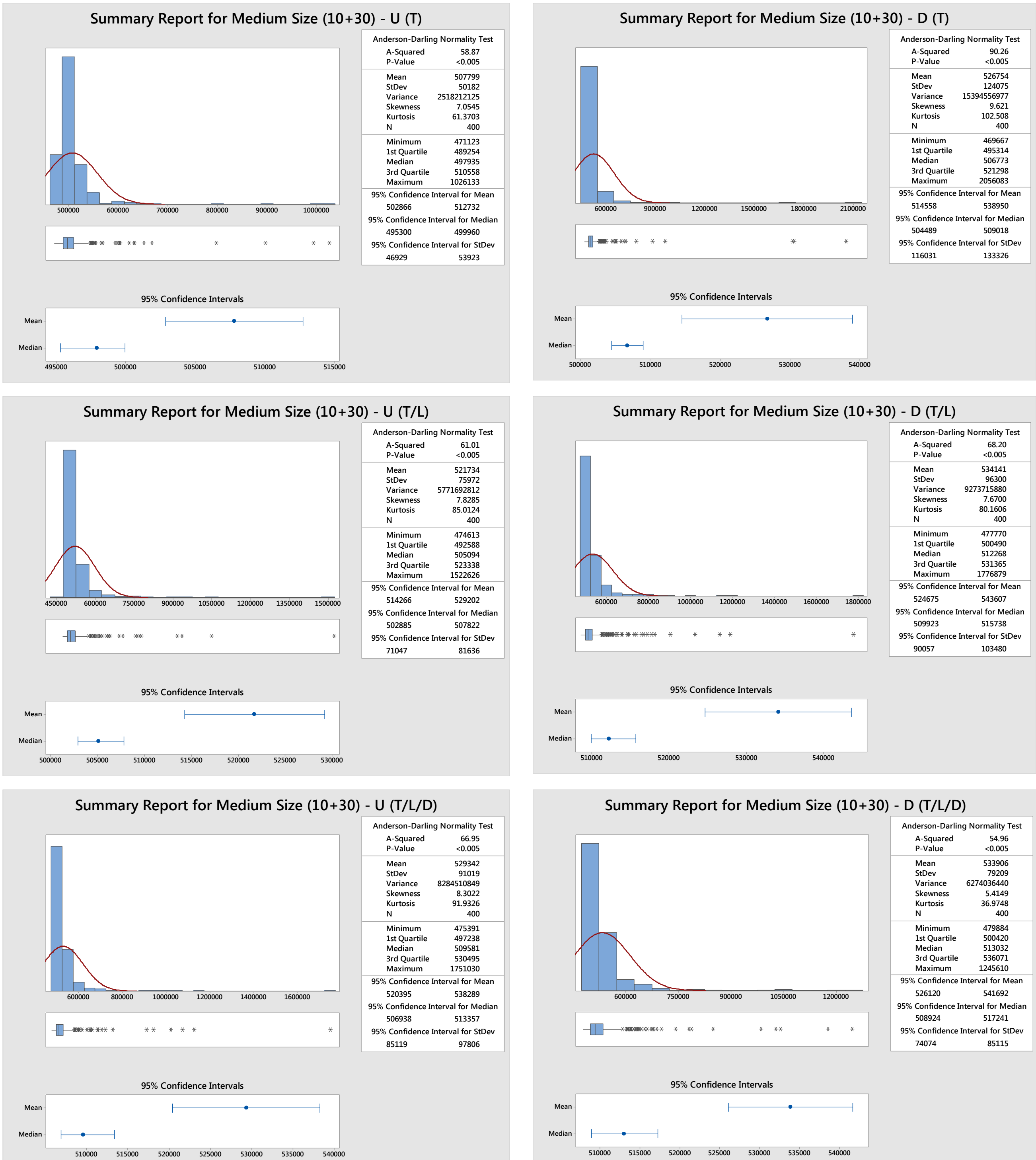


Figure 4. Medium Size Instance Optimization-simulation Results

Table 3 displays the best simulation results for the medium size instance. There are some similarities in the solution structures for all six scenarios, such as barges #4, #20, and # 22 all assigned to Terminal 1. However, no solutions have the exact same structures as shown in small size instance. Based on our previous research, small size instances usually obtained the optimal solutions in the CPTAP GA, which is not the case for medium size instances. The maximum CPU time is no more than thirty-seven minutes, which is a reasonable amount of time to wait for an optimization-simulation solution on cargo prioritization and terminal allocation when the waterway is disrupted.

Table 3. Medium Size Instance Simulation Results

Scenario	**Minimum Simulation Result ($)**	**Best Solution**	**CPU Time (s)**
Up (Travel)	471122.675	Terminal 1: 20 4 9 22 Terminal 2: 12 19 8 11 Terminal 3: 28 18 10 Terminal 4: 24 1 29 Terminal 5: 2 6 26 Terminal 6: 21 27 25 Terminal 7: 3 17 5 15 7 Terminal 8: 30 13 14 Terminal 9: 16 23	1081.997
Up (Travel & L/D)	474612.872	Terminal 1: 20 4 9 22 Terminal 2: 19 8 11 Terminal 3: 28 18 Terminal 4: 24 17 1 23 Terminal 5: 2 6 26 Terminal 6: 27 21 25 29 Terminal 7: 3 5 15 7 Terminal 8: 12 30 13 14 Terminal 9: 16 10	1119.292
Up (Travel & L/D & Delay)	475391.381	Terminal 1: 20 4 22 Terminal 2: 12 19 8 11 Terminal 3: 28 18 Terminal 4: 24 17 1 Terminal 5: 2 6 26 Terminal 6: 27 21 25 29 Terminal 7: 3 5 7 15 14 Terminal 8: 9 30 13 Terminal 9: 16 10 23	1159.701
Down (Travel)	469667.272	Terminal 1: 20 4 9 22 Terminal 2: 12 19 8 11 Terminal 3: 28 18 Terminal 4: 24 17 1 Terminal 5: 2 6 26 Terminal 6: 27 21 25 29 Terminal 7: 3 5 7 15 Terminal 8: 30 13 14 Terminal 9: 16 10 23	2197.260

Down (Travel & L/D)	477769.664	Terminal 1: 20 4 9 22 Terminal 2: 12 19 8 11 Terminal 3: 28 18 Terminal 4: 24 17 1 23 Terminal 5: 2 6 26 Terminal 6: 27 21 25 29 Terminal 7: 3 5 16 15 7 Terminal 8: 30 13 14 Terminal 9: 10	1450.289
Down (Travel & L/D & Delay)	479883.850	Terminal 1: 20 4 9 22 Terminal 2: 12 19 8 11 Terminal 3: 1 28 18 10 Terminal 4: 24 6 17 29 Terminal 5: 2 26 Terminal 6: 27 21 25 Terminal 7: 3 5 7 15 Terminal 8: 30 13 14 Terminal 9: 16 23	1082.621

4.3 Large Size Instance Results

The integrated optimization-simulation CPTAP programming code cannot reach a solution for a large size problem instance after running for forty-eight hours. Therefore, an alternative approach is employed where we ran four 100 simulation iterations separately and combine the results together to obtain the four hundred simulation iteration results. Minitab is again used to analyze the combined four hundred smallest value losses and identify the minimum one with a value loss of $713, 395. According to Figure 5, the distribution of the results are more spread out compared to small and medium size instance simulation results, likely due to the larger search space of the bigger problem size. The decreasing kurtosis value from small to large size instance shows the same conclusion where the flatter peak shape of the large size instance has less simulation results that can reach the obtained minimum value loss. More outliers are observed, and 75% of the results produce the value loss within a 15.2% increase from the minimum value loss.

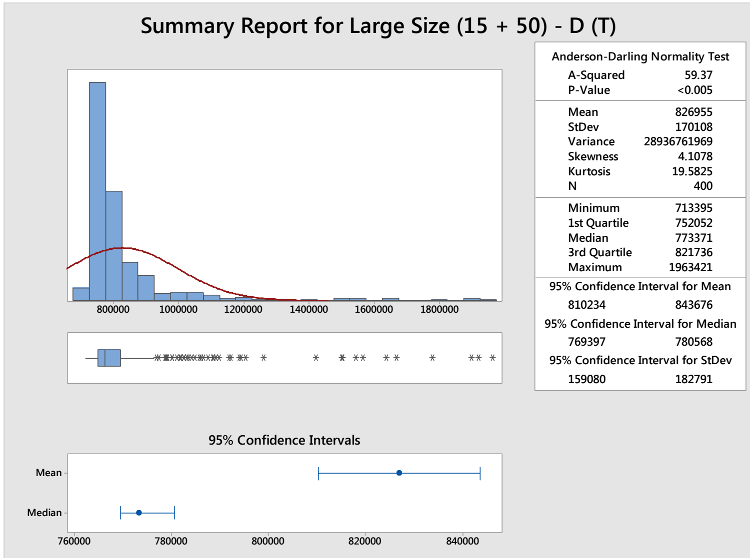


Figure 5. Large Size Instance Optimization-simulation Results

5. Impacts/Benefits of Implementation

In addition to providing guidance on cargo prioritization under uncertainty, this project can be used to identify infrastructure that exhibits low resiliency in terms of modal capacity to potential attacks or natural disasters against inland waterway transportation systems. Inland waterways transport over 600 million tons of cargo each year. A catastrophic event on the rivers could disrupt commerce for an extended period of time. It is important to pre-plan for this type of event, enable coordination between industry and governmental groups, and provide knowledge of where the system lacks resilience to recover from such an event. Inland waterways are a national asset for many reasons, including the $70 billion dollars of cargo that are transported annually, the impact of reducing congestion on already over-crowded highways and railways, and the tens of thousands of jobs associated with this transportation mode.

6. Recommendations and Conclusions

Expanding our previous research on deterministic inland waterway disruption response, we developed a Monte Carlo-based simulation optimization approach to handle uncertain parameters in the CPTAP model. Different scenarios of waterway transportation were considered, and the barge speeds were generated from real data to represent the random scenarios. We applied the optimization-simulation CPTAP model to small, medium and large size problem instances. Minimum value losses and corresponding solution structures can be obtained within a reasonable CPU time for small and medium size instances in one programming run. An alternative approach with multiple programming runs is adopted for large size instance to obtain the minimum value loss and its solution structure. We observe that distributions of the simulation results are getting more and more spread out but the majority of the results are close to the minimum value loss for all instances with different sizes.

References

Budipriyanto, A., Wirjodirdjo, B., Pujawan, I. and Gurning, S. (2015). Berth allocation problem under uncertainty: A conceptual model using collaborative approach. *Procedia Manufacturing*, *4*, 429-437.

Budipriyanto, A., Wirjodirdjo, B., Pujawan, I. and Gurning, S. (2017). A simulation study of collaborative approach to berth allocation problem under uncertainty. *The Asian Journal of Shipping and Logistics*, *33* (3), 127-139.

Dragovic, B., Tzannatos, E. and Park, N. (2016). Simulation modelling in ports and container terminals: Literature overview and analysis by research field, application area and tool. *Flexible Services and Manufacturing Journal*, *29* (1), 4-34.

Legato, P. and Mazza, R. (2008). Simulation-based optimization for the quay crane scheduling problem. *Proceedings of the 2008 Winter Simulation Conference*.

Legato, P., Mazza, R. and Trunfio, R. (2010). Simulation-based optimization for discharge/loading operations at a maritime container terminal. *OR Spectrum*, *32*, 543-567.

Legato, P., Mazza, R. and Gulli, D. (2014). Integrating tactical and operational berth allocation decisions via simulation-optimization. *Computers & Industrial Engineering*, *78*, 84-94.

Liu, C., Xiang, X., Zhang, C. and Zheng, L. (2016). A decision model for berth allocation under uncertainty considering service level using an adaptive differential evolution algorithm. *Asia-Pacific Journal of Operational Research*, *33* (6), 1-28.

Sacone, S. and Siri, S. (2009). An integrated simulation-optimization framework for the operational planning of seaport container terminals. *Mathematical and Computer Modelling of Dynamical Systems*, *15* (3), 275-293.

Tong, J. and Nachtmann, H. (2017). Cargo prioritization and terminal allocation problem for inland waterway disruptions. *Maritime Economics & Logistics*, *19* (3), 403-427.

Xiang, X., Liu, C. and Miao, L. (2017). A bi-objective robust model for berth allocation scheduling under uncertainty. *Transportation Research Part E*, *106*, 294-319.

Xu, Y., Chen, Q. and Quan, X. (2012). Robust berth scheduling with uncertain vessel delay and handling time. *Annals of Operations Research*, *192* (1), 123-140.

Zeng, Q. and Yang, Z. (2009). Integrating simulation and optimization to schedule loading operations in container terminals. *Computers & Operations Research*, *36*, 1935-1944.

Zhen, L. (2015). Tactical berth allocation under uncertainty. *European Journal of Operational Research*, *247*, 928-944.