Proceedings of the 2023 Winter Simulation Conference
C. G. Corlu, S. R. Hunter, H. Lam, B. S. Onggo, J. Shortle, and B. Biller, eds.

SYSTEM SIMULATION AND MACHINE LEARNING-BASED MAINTENANCE OPTIMIZATION FOR AN INLAND WATERWAY TRANSPORTATION SYSTEM

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ABSTRACT

To continue operations of the inland waterway transportation system (IWTS), the interconnected infrastructure, such as locks and dam systems, must remain in good operating condition. However, as the IWTS ages, unexpected disruptions increase, causing significant transportation delays and economic losses. To evaluate the impacts of IWTS disruptions, a Python-enhanced NetLogo simulation tool is developed, where extreme natural events are also considered and characterized by a spatiotemporal model. Utilizing this tool, optimal maintenance strategies that maximize cargo throughput on the IWTS are determined via deep reinforcement learning. A case study of the lower Mississippi River system and the McClellan-Kerr Arkansas River Navigation System is conducted to illustrate the capability of the developed simulation and machine learning-based method for IWTS maintenance optimization.

1 INTRODUCTION

The inland waterway navigation system is a critical component of the United States (U.S.) transportation network and facilitates the safe and efficient freight movement of agricultural, coal, petroleum, and chemical commodities. For example, the Mississippi River System, the primary inland waterway navigation system in the U.S., supports exports markets from grain producers from Baton Rouge through New Orleans, all the way to Myrtle Grove, LA. It serves as a crucial artery for the export of a significant portion of U.S. corn and soybean products. This region handles a staggering 57% of U.S. corn exports by volume, valued at \$4.8 billion, and 59% of U.S. soybean exports, totaling \$12.4 billion. Furthermore, it also accounts for 55% of soybean meal exports and an astounding 72% of distiller's dried grains with solubles exports, making it a pivotal hub for the agricultural export market (US Department of Agriculture 2019).

Although agricultural exports significantly contribute to the U.S. balance of trade, the industry is facing some challenges. One major challenge is the aging and diminishing condition of the inland waterway infrastructure. As time passes, the system is not as effective or resilient as it used to be. Indeed, reduction in this cost-effective mode of transport will make it increasingly difficult for U.S. corn and soybean exporters to maintain their competitive position. To restore the inland waterway navigation system to its optimal capacity and mitigate the risk of major disruptions, rehabilitation and construction efforts are urgently needed (US Department of Agriculture 2019).

In certain regions of the inland waterway navigation system, lock and dam systems are utilized to uphold the required navigation channel depths, enabling towboats and barges to navigate from origin to destination along the rivers. Since a malfunction in a lock's operation can have a considerable effect on the transportation of barges, announcements about necessary maintenance causing scheduled outages are typically made months or even years in advance. This allows impacted shippers who rely on waterways to adjust their commodity inventories or take other

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measures to prepare for the upcoming service disruption. However, unscheduled lock closures caused by weather, accidents, or mechanical failures may cause significant disruptions, to which carriers and shippers do not have any opportunity to quickly respond. To tackle these challenges, it is imperative to leverage cutting-edge technologies and robust infrastructure. One key technology that can prove useful in this regard is predictive maintenance that proactively detects and troubleshoots potential issues, thereby mitigating the negative impact of unscheduled outages of lock and dam systems. Moreover, upgrading and proactively repairing aging locks can greatly reduce such impact on inland waterway-dependent businesses (US Department of Agriculture 2019).

Table 1 provides an overview of the lockages of vessels in a waterway for the years 2000, 2010, and 2017 (US Department of Agriculture 2019). The data reveals a substantial decrease in the total number of vessels, which dropped from 231,145 in 2000 to 118,647 in 2017, along with a corresponding reduction in lockages from 160,640 in 2000 to 113,014 in 2017. Additionally, this table shows an increase in commercial lockages from 69.9% in 2000 to 79.9% in 2017, indicating a growth in commercial vessel traffic within the waterway. However, this increase in commercial lockages coincided with an increase in vessel delay during lockages from 90.0 minutes in 2000 to 121.8 minutes in 2017.Furthermore, the percentage of vessels experiencing some delay during lockages increased from 20.0% in 2000 to 53.0% in 2017. These findings suggest potential concerns regarding the waterway's operation efficiency and economic implications.

Table 1: Lockage and vessel delay in the Mississippi River (US Department of Agriculture 2019).

Year	Total Vessels	Total Lockages	Commercial Lockages	Average Delay (minutes)	Percentage of Vessels Delayed
2000	231,145	160,640	69.9%	90.0	20.0%
2010	139,768	109,205	68.2%	81.0	19.0%
2017	118,647	113,014	79.9%	121.8	53.0%

This work develops a Python-enhanced NetLogo simulation tool to evaluate the effects of disruptions caused by lock closures. Based on the simulation tool, optimal maintenance strategies that maximize the throughput of an inland waterway transportation system (IWTS) are determined via deep reinforcement learning (DRL). A case study on the lower Mississippi River and the McClellan–Kerr Arkansas River Navigation System (MKARNS) is conducted to illustrate the capability of the developed simulation and machine learning-based method for IWTS maintenance optimization. The developed methodology will assist operators and stakeholders in maintaining the waterway's effectiveness and ensuring the safety and efficiency of vessel transportation.

The remainder of this paper is organized as follows. Section 2 presents a literature review of related works. Section 3 describes the research problem and related practical considerations. Section 4 provides the details of the developed simulation and decision-making tool built upon an open-source platform. Section 5 presents a case study to illustrate the capabilities of the developed tool. Finally, Section 6 draws conclusions and outlines future research.

2 LITERATURE REVIEW

Extensive studies have been conducted on the performance evaluation and efficiency improvement of an aging IWTS. The technical aspects of these studies are on traffic modeling, economic impacts, and performance optimization.

Zhou et al. (2019) compared different maritime traffic models and emphasized two major questions related to model development in this area; (i) what kind of vessel behavior is under study and (ii) how these behaviors should be modeled. To answer these questions, the inherent, static characteristics of vessels and those external factors that change these characteristics need to be considered. Most maritime traffic models consider each vessel as an agent and implement agent-based modeling to simulate the behavior of those vessels (Zhou et al. 2019). Carroll and Bronzini (1973) developed a computer simulation model incorporating the information and characteristics of commodity flows and fleets to associate each tow to commodities and simulate the movement of these tows through locks, ports, and gates. Taylor et al. (2005) developed a simulation-based scheduling system and found that due to the availability of calendar events and the ability to schedule multiple components with different attributes, a simulation model offers an excellent platform for informed decision-making on barge dispatching and boat assignments. Biles et al. (2004) combined Geographic Information Systems (GIS) with an AutiMod model of barge traffic and an Arena model for ocean-going vessel transit. Their results demonstrated that geographically referenced data could add more values to simulation models for modeling realism and initializing the process.

Oztanriseven and Nachtmann (2020) investigated the economic impacts of an IWTS using their maritime transportation simulator (i.e., MarTranS) that integrates agent-based modeling, discrete event simulation, system dynamics, and multiregional input-output analysis. To demonstrate MarTranS, a case study of the MKARNS was conducted, revealing the system is not sustainable without future investment in the river. Azucena et al. (2021) developed a simulation model to investigate the impacts of waterway disruptions on multimodal transportation systems by predicting the occurrences of extreme natural events (e.g., flooding) using a spatiotemporal model.

Regarding IWTS performance optimization, the related problems can be tackled from different angles (Bu and Nachtmann 2021): (i) intermodal transportation (e.g., intermodal facility location), (ii) terminal operations (e.g., berth allocation problem), (iii) barge management (e.g., barge capacity optimization), (iv) container-on-barge (e.g., environmental impact assessment), and (v) ship routing. For example, Nur et al. (2020) developed a multi-commodity, multi-time period model for minimizing the supply chain cost using the Benders decomposition algorithm. They studied both short-term operational decisions (e.g., trip-wise tow boat and barge assignment) and mid-term supply chain decisions (e.g., inventory management and transportation mode). Zhou et al. (2021) reviewed the recent works related to the integration of simulation and optimization of maritime logistics and pointed out five different modes of integration: (i) simulation for optimization output, (ii) simulation for optimization input, (iii) simulation optimization iteration, (iv) simulation-based optimization, and (v) optimization-embedded simulation. Especially, Bush et al. (2003) applied the third method to a barge traffic problem. Their objective is to minimize the cost associated with barge movement, including the distance traveled and the type of boat or tow that carries the barges. The optimization result is sent to a simulation model to ensure that the routing defined by the optimization model is feasible in the lower Mississippi River. This process continues until a stopping condition is met. Kulkarni et al. (2017) also applied the third method on port operations where the simulation model analyzed the performance of the gates in the port, and the optimization model investigated an efficient lane management policy for the gate system. In this work, we will also focus on simulation optimization with a goal of maximizing the throughput of an IWTS by determining the optimal sequence of maintenance actions on locks.

In practice, an optimal scheduling problem involving a series of locks is quite complex and is not solvable in polynomial time (Passchyn 2016). Recent studies have used reinforcement learning (RL) as a solution alternative. For example, Hart et al. (2022) extracted vessel behavior data from the Automatic Identification System and formulated the reward function based on safe navigation. Their model, which can apply to different scenarios, uses a stochastic process to model the leading trajectory and dynamics of the river. In this work, we will take advantage of simulation and RL in making maintenance decisions for locks. To the best of our knowledge, this is the first attempt in the area of inland waterway transportation and logistics.

3 PROBLEM DESCRIPTION AND PRACTICAL CONSIDERATIONS

This work considers the operation of an IWTS involving waterways, ports and locks. Through simulation and optimization, the optimal sequence of maintenance and repair actions on these locks over a specific planning horizon is determined to maximize the throughput of the IWTS for the same period.

The simulation model allows users to modify the cargo that a barge carries and the distribution of each commodity type based on demands. In addition, the number of barges transported by each towboat can be specified by the user before a simulation run. During simulation, the vessels are characterized by a set of variables, such as origin, destination, current location, distance traveled, speed, vessel category, product type, product weight, extreme events encountered, and total delay. As part of outputs of the simulation model, barge movement should be tracked through statistical analyses of these variables.

The successful execution of vessel movement simulation requires meticulous consideration of various factors. These factors include source and sink nodes (i.e., origin and destination), simulation time, tow speed, and lock status. It is worth pointing out that along navigable waterways, there are several sites where the gage heights are checked for measuring water levels in real time. The measurements help operators make informed decisions about vessel movement (i.e., proceed or halt based on the current water level). An algorithm needs to be developed to ensure that the vessels adhere to a set of interaction rules between origin and destination, navigation time and speed, and other agents. In this work, each vessel was programmed to always choose the shortest path according to its origin and destination during simulation while taking into account factors such as waterway conditions, vessel speed, and other constraints. These complex considerations and interactions are critical in creating an advanced simulation environment that reflects the real-world dynamics of vessel movements in waterways.

Another set of key considerations is related to repairs and preventive maintenance of locks. In this work, a repair crew responsible for repairs, preventive maintenance, and inspections of locks is considered under various practical aspects. An intuitive logic was included to handle situations where multiple lock failures occur simultaneously. In such cases, an automatic assignment mechanism is employed, which prioritizes repair on the lock with the highest importance. This prioritization strategy ensures that critical lock failures are fixed promptly with the goal of minimizing downtime and potential disruptions in the system's operation. It is assumed that a repair action is perfect, which restores a lock's operating condition to as good as new. Another consideration is the minimum time interval between consecutive preventive maintenance actions on each lock. The repair and preventive maintenance times are random due to the unpredictable nature of these tasks. Moreover, it is assumed that each inspection can be completed quickly (e.g., one day), and ongoing repair or preventive maintenance tasks cannot be interrupted. Once the repair crew is assigned to a lock, they become temporarily unavailable until the task is completed.

The study considers a fixed annual budget for preventive maintenance and repair tasks. This budget constraint adds another layer of complexity to the repair and maintenance planning problem. Indeed, to maximize the throughput of the entire IWTS, the criticality of each lock must be taken into account to prioritize the tasks of the repair crew with limited recovery resources. In other words, repair and preventive maintenance need to be considered in a comprehensive manner by incorporating a collection of critical information, such as the available resources and criticality of different locks.

4 METHODOLOGY

To simulate the operation of an IWTS, time-varying waterway conditions (e.g., water level), lock status, vessel movement, and availability of maintenance crew must be modeled. In addition, an efficient optimization technique needs to be implemented to maximize the throughput of the IWTS. Figure 1 shows the flowchart of the developed simulation and DRL tool. More details about the related models and optimization aspects are elaborated next.

4.1 Spatiotemporal Model for Water Level Prediction

At the core of the simulation tool is its capability to predict the gage height at a measurement site. A Spatio-Temporal Bayesian Modelling (spTimer) method was utilized to capture the complex interplay of spatial and temporal correlations among the selected measuring sites considering seasonal variations. The key model is a hierarchical auto-regressive Gaussian Process considering spatiotemporal random effects with Matérn spatial correlation decay (Azucena et al. 2021). This model is estimated with Bayesian methods using Gibbs sampling as implemented in the spTimer R package (Bakar and Sahu 2015). For the linear coefficients, time auto-correlation parameters, and pure variance effects, flat priors recommended as default in spTimer package were selected. Specifically, we used Normal priors with arbitrarily large variance hyperparameters for the linear coefficients and time auto-correlation parameter and Gamma priors for the pure variance effects. For the spatial correlation decay parameters, Gamma distributions were utilized and tuned to attain a sample acceptance rate of around 40%.

One advantage of this method is its potential to infer gage height data from sites of interest where actual measurements are not available. The method utilizes the data from observed sites to generate interpolations for other locations along the same river. It enables stakeholders to estimate water levels in areas where direct measurements are unavailable and to predict disruptions at different waterway locations (Azucena et al. 2021).

4.2 Modeling the Effects of Repair and Preventive Maintenance

In practice, failures of locks are unavoidable due to aging. In this work, the distribution of locks' time-between-failures was determined based on historical data. To reduce the negative impact of lock failures on the throughput of IWTS, preventive maintenance can be performed before locks fail. Such actions may reduce the ages and/or failure rates of locks to different extents. Especially, a perfect preventive maintenance action (or repair) will make a lock go back to its good-as-new state, while an imperfect preventive maintenance action (or repair) will bring the lock to somewhere between its good-as-new state and bad-as-old state.

Figure 1: Flowchart of the developed simulation and DRL tool.

In real-world applications, a repair action is mandatory when a lock fails. In this work, each repair action was assumed to be perfect, which resets the age and failure rate of a lock. On the other hand, each preventive maintenance action was assumed to be imperfect, which resets the age of a lock but makes its failure rate increase faster. Such imperfect improvement can be reflected by adjusting the scale parameter of the lock's probability distribution of time-between-failures. For example, if the time-between-failures of a renewed lock follows a three-parameter Gamma distribution $Gamma(\alpha_0, \beta, \gamma)$ with a probability density function:

$$f(t;\alpha_0,\beta,\gamma) = \frac{(t-\gamma)^{\beta-1}e^{(t-\gamma)/\alpha_0}}{\Gamma(\beta)\alpha_0^{\beta}}, \quad t > \gamma \tag{1}$$

The effect of a preventive maintenance action on the lock's future time-between-failures can be characterized by:

$$\alpha_{i+1} = \delta_m \alpha_i \tag{2}$$

where the parameter $0 < \delta_m < 1$ represents the proportional reduction in the scale parameter α_{i-1} after the ith preventive maintenance action. Clearly, the failure rate after the ith preventive maintenance increases faster than that after the previous maintenance action. Note that α is reset to its original value α_0 after a perfect repair.

4.3 Development of the Agent-based Simulation Model

Developing agent-based models (ABMs) has become a popular way of studying complex adaptive systems due to their capability to capture the interactions of diverse entities exhibiting complex behaviors. NetLogo is an open-source environment for designing and testing ABMs, implemented primarily in Java and Scala. It includes a range of functions and methods to support the rapid development of spatially explicit ABMs. The advancement of our model is rooted in its ability to integrate four different extensions of NetLogo: GIS (Geographic Information System), NW (Networks), and R (R Language for Statistical Analysis).

GIS data can be quite useful for integrating more "realistic" models and linking them to particular locales. By combining numerous layers of data, we are offered a visually appealing depiction of information. Indeed, NetLogo becomes a useful tool for geographical analysis and simulation when GIS data is used. Technically, the GIS extension allowed us to import vector data in the form of ESRI shapefiles and create several maps (e.g., the Mississippi River and MKARNS) in our simulation tool. In addition, we leveraged NetLogo's graphical user interface to create a two-dimensional "world" for our simulation. A grid of patches represents this world, each with a unique set of coordinates (pxcor and pycor). We imported the GIS maps to create a graph of nodes and links, which we then used to model vessel movement (Azucena et al. 2021). To track vessel movement in the simulation environment, "time" must be defined. In a NetLogo model, a "tick" serves as a unit of time (e.g., seconds or minutes in other contexts), which ensures the uniformity and comparability in modeling results regardless of the hardware or software used. In this study, one hour equals four ticks.

Complicated studies on a network can be carried out with the help of NetLogo's NW-Extension. It provides a wide range of sophisticated functions, such as the capacity to keep track of previously calculated pathways, which maximizes the effectiveness of subsequent analyses. The NW extension primitives inherently regard all turtles and links as essential parts of the existing network; therefore, no further steps are necessary in the sense of treating the entire system as a single network.

Regarding the coding effort, the R extension offers an easy way to visualize and analyze data, providing an alternative to the conventional process of writing data to files and then reading them back. However, its greatest utility comes from using R to execute agent decision-making. Moreover, this work also uses the pyNetLogo library, which allows NetLogo to be controlled through the Python programming language. Python is a popular language with a broad range of libraries to support ABM development and testing. pyNetLogo extends the benefits of a specialized analysis environment to a broader problem setting, making it a useful complement to existing connectors (Jaxa-Rozen and Kwakkel 2018).

It is worth pointing out that our model represents a significant advancement in the field of transportation modeling, as it integrates the latest technologies and techniques to simulate real-world scenarios in an IWTS. It helps the decision maker quantify the criticality of locks by considering lock usage, historical maintenance records, and operational impacts of failures. Moreover, the model is robust and allows for flexible customization and scaling.

4.4 Use of DRL for Maintenance Optimization

DRL merges the power of deep learning and reinforcement learning to enable intelligent agents to learn decision-making skills by receiving feedback from their environment. By treating the environment as a Partially Observable Markov Decision Process (POMDP), DRL empowers agents with the ability to adapt to uncertain and dynamic situations, making it a highly flexible and versatile method for training autonomous agents.

OpenAI Gym (Brockman et al. 2016) offers a standardized environment that enables easy experimentation with reinforcement learning algorithms. In addition, it provides a diverse set of environments with varying levels of complexity, along with a flexible framework for creating custom simulations for interactive problem-solving. In this work, we developed a unique environment tailored for evaluating and training a Maskable Proximal Policy Optimization (M-PPO) algorithm (Huang and Ontañón 2020), which utilizes flags to identify feasible actions based on the simulation environment as constraints and validity conditions. Since our problem domain involves resource allocation and budget constraints, they can be readily translated into action masks to ensure valid actions during simulation.

The state represents the agent's perception of the environment and is essential in determining the reward and choosing the following action. We represent the state space in this study as a binary vector, where each element corresponds to a lock in the environment. A value of "1" indicates an operational lock, while "0" indicates a failed lock. The action space consists of three tasks, indexed as 0, 1, and 2, representing no action, inspection, and preventive maintenance. Since repairs are mandatory, they are not included as an option in the action space.

The advantages of updating the budget at every time step when the repair crew is active, and incorporating it into the optimization problem for maximizing the throughput of the IWTS, are manifold. The optimal maintenance planning problem to be solved via DRL can be formulated as:

$$
\begin{aligned}
\max_{Actions_{1:t}} \quad & Reward_t = Reward_{t-1} - \sum_{l \in L} [I\{Fd_{lt} > St\} \cdot Ndb_{lt}(\{PM_{lu}, Ins_{lu}, R_{lu}\}_{u=0}^{t-1}) & \\
\text{s.t.} \quad & PMt_{l,j+1} - PMt_{l,j} \geq PMR & \forall l \in L,\ \forall t \in T \\
& R_{lt} \leq (1 - S_{it}) & \forall l \in L,\ \forall t \in T \\
& R_{lt} \leq AR_t & \forall l \in L,\ \forall t \in T \\
& Ins_{lt} \leq AR_t & \forall l \in L,\ \forall t \in T \\
& PM_{lt} \leq AR_t & \forall l \in L,\ \forall t \in T \\
& Bud_t = Bud_{t-1} - RC^{cost} \cdot R_{l,t-1} - Ins^{cost} \cdot Ins_{l,t-1} - PM^{cost} \cdot PM_{l,t-1} & \forall t \in T \\
& R_{lt} \cdot (RC^{cost} - Bud_t) \leq 0 & \forall l \in L,\ \forall t \in T \\
& Ins_{lt} \cdot (Ins^{cost} - Bud_t) \leq 0 & \forall l \in L,\ \forall t \in T \\
& PM_{lt} \cdot (PM^{cost} - Bud_t) \leq 0 & \forall l \in L,\ \forall t \in T
\end{aligned} \tag{3}
$$

where L, B, T , RC^{cost}, Ins^{cost} and PM^{cost} are sets of locks, barges, time steps, and the costs for repair, inspection and preventive maintenance, respectively. The failure duration for each lock, denoted by Fd_{lt}, can be altered, and St represents a time threshold that is determined by an expert. This threshold is utilized to determine if a delay should be considered significant enough to apply a penalty. Ins_{lt}, PM_{lt}, and R_{lt} are binary variables taking "1" when inspection, preventive maintenance, or repair have been done for lock l at time t and "0" otherwise. S_{lt} and AR_t are also binary parameters representing the status of a lock and the availability of the repair crew at time t, respectively. The first constraint specifies that the points in time, $PMt_{l,j}$ and $PMt_{l,j+1}$, of two consecutive preventive maintenance actions on lock l should be at least PMR days apart. The second constraint specifies that a repair is mandatory if there is a failed lock. The third, fourth and fifth constraints check the availability of the repair crew before repair, inspection and preventive maintenance tasks, respectively. The sixth constraint updates the remaining budget in every step based on the actual costs incurred from the execution of tasks, and the next three constraints check if the budget is sufficient for a repair, inspection or preventive maintenance on lock l to ensure that the project stays within the budget limits. Finally, the objective function maximizes the total reward, which is equivalent to minimizing the number of barges (Ndb_{lt}) that experience delays when the failure duration of the corresponding lock is longer than the predefined threshold St. It should be mentioned that the number of disrupted barges for each lock at time t is contingent upon the cumulative impact of all actions $\{PM_{lu}, Ins_{lu}, R_{lu}\}_{u=0}^{t-1}$ undertaken up to time $t-1$.

5 CASE STUDY

This study considers the Mississippi River system and MKARNS, including fifteen locks and eight ports: Tulsa, Fort Smith, Little Rock, Baton Rouge, Helena, Memphis, and St. Louis. There are twenty-four sites along this IWTS. At each site, the system checks gage heights in real time. The ultimate goal of the study is to optimize the sequence of preventive maintenance and repair actions on these locks over a one-year planning horizon to maximize the system's throughput.

5.1 Data

In this work, three main types of data were utilized for the development of the simulation and decision-making models. Especially, the model parameters related to vessel traffic conditions, water levels, and lock operations impacting the IWTS' throughput are the most important.

- The data for traffic conditions and waterway usage from the Civil Works Business Intelligence Navigation System helps understand the volume of waterway traffic and identify areas of congestion or inefficiency (US Army Corps of Engineers Lock Performance Monitoring System 2023). In this work, this information was used to set up the simulation environment and as the input for the optimization model.
- The comprehensive dataset (over 315 thousand observations in total) consisting of hourly gage height measurements at eighteen sites from February 22, 2016 to February 21, 2018 (Azucena et al. 2021) provides critical information about the navigability of waterways. In this work, the data along with waterway

disruptions (i.e., floods and droughts) were used to develop the spatiotemporal statistical model for water level simulation.

- The U.S. Army Corps of Engineers (USACE) Open Data for Locks provides useful information of lock closures due to scheduled and unscheduled maintenance (US Army Corps of Engineers 2019). This data is publicly available, allowing for conducting transparent and reproducible research. In this work, the data was used to identify the patterns and trends of lock closures, which serve as the basis for maintenance decision making.

Figure 2 shows the graphical user interface of the developed NetLogo simulation tool when simulation proceeds under a specific vessel traffic scenario of the Mississippi River system and MKARNS.

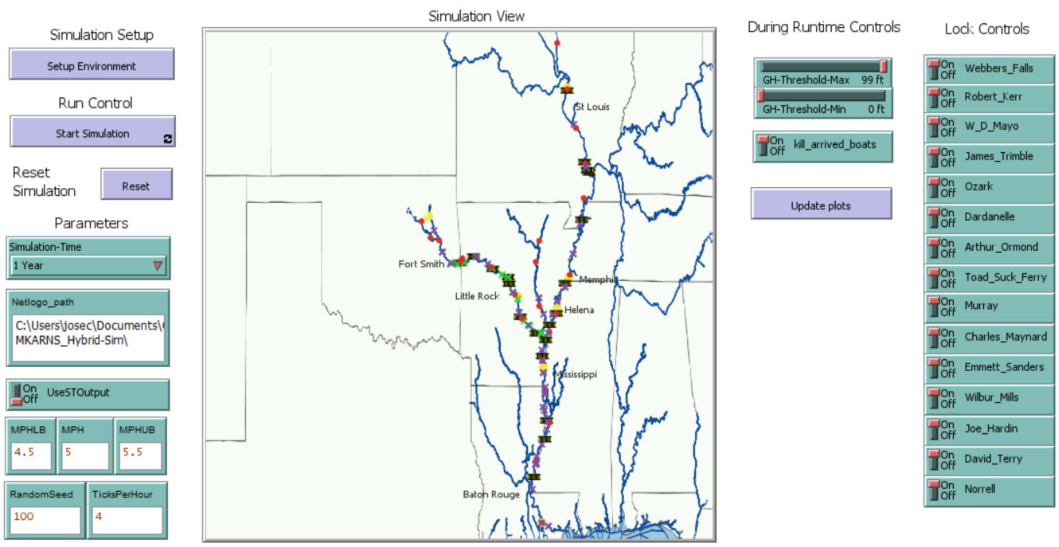

Figure 2: Graphical user interface of the developed NetLogo simulation tool.

Azucena et al. (2021) took a rigorous approach to validate a spatiotemporal model developed based on the gage height data. Figure 3 shows the water level prediction with a 90% point-wise confidence band against the actual observed data in one selected site. Clearly, the prediction captures the seasonality and trend of the actual data, indicating that the model as part of the simulation tool is adequate for water level prediction.

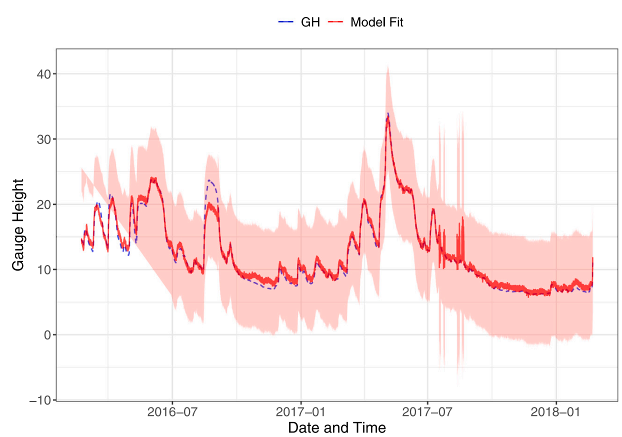

Figure 3: Water level prediction (in feet) for one site using the spatiotemporal model (Azucena et al. 2021).

A numerical experiment was conducted to fit the probability distributions of time-between-failures and closure duration for locks based on the data from the Civil Works Business Intelligence Navigation System (US Army Corps of Engineers Lock Performance Monitoring System 2023). Table 2 shows the best fits for these probability distributions. For the effect of imperfect preventive maintenance, we assumed that the proportional reduction $\delta_m \sim Uniform(0.8, 1)$.

Table 2: The probability distributions of failure, repair and preventive maintenance time (days).

Time	Distribution	α	β	γ
Time-between-failures of a lock	Three-parameter Gamma	0.486	78.76	1.99
Repair time	Exponential	1/2.82	–	–
Preventive maintenance time	Exponential	1/0.94	–	–

5.2 Numerical Results

Table 3 shows the key parameters in optimizing the sequence of maintenance actions on the locks. By carrying out simulation and executing DRL, the cumulative reward, remaining budget, number of operable locks, locks' failure rates, availability of repair crew, and number of tasks performed (i.e., inspection, preventive maintenance, and repair), and the optimal sequence of actions were obtained.

Table 3: Key parameters used in maintenance and repair optimization.

Parameter	Value	Description
T	365 days (1 year)	Planning horizon
Bud_0	\$50,000,000	Total budget for the planning horizon
RC^{cost}	\$150,000	Cost of each repair
Ins^{cost}	\$1,000	Cost of each inspection
PM^{cost}	\$50,000	Cost of each preventive maintenance (PM)
PMR	15 days	Minimal time interval between two consecutive PMs on each lock

Figure 4 shows the six performance measures over time. According to Equation (2), the reward function (upper left) is decreasing over time as more barges got delayed due to lock failures causing penalty. The DRL algorithm tried to keep the reward as high as possible by determining the optimal sequence of repair and preventive maintenance actions based on the criticality of different locks at different times. As more actions were taken, the available budget decreased (upper right). The results presented in the center show the number of operable locks and the failure rates of the fifteen locks over time, respectively. The availability of the repair crew and and the cumulative numbers of tasks the crew performed are given in the figures at the bottom. The information can be used as the basis for allocating resources and scheduling appropriate actions to reduce the number of lock failures in a holistic way. To better illustrate the interaction between the repair crew and the locks, Figure 5 provides a closer look at the availability of the repair crew and the failure rates of two locks in the fourth month (day 90 - day 120). One can see that the crew tried their best to reduce the failure rates of locks by conducting preventive maintenance and repair failed locks. However, due to their low availability, some failed locks may not be repaired immediately.

A sensitivity analysis of the initial budget was conducted. Table 4 shows how changes to the original budget may affect the crew's subsequent actions. Table 5 shows the resulting percentage of time that each lock remains open over the course of a year. It is worth pointing out that such analyses provide insights into the adequacy of the initial budget and help identify the operation bottleneck(s) in achieving a desired system performance level.

6 CONCLUSION

The developed Python-enhanced NetLogo simulation tool provides a realistic and flexible way to study the operation of an IWTS and reduce the negative economic impact of disruptions. Especially, by taking advantage of a spatiotemporal model capable of describing water level variation and probabilistic models for lock failures, the simulation tool can assess the performance of the IWTS under various scenarios. Moreover, the DRL approach is indeed an efficient

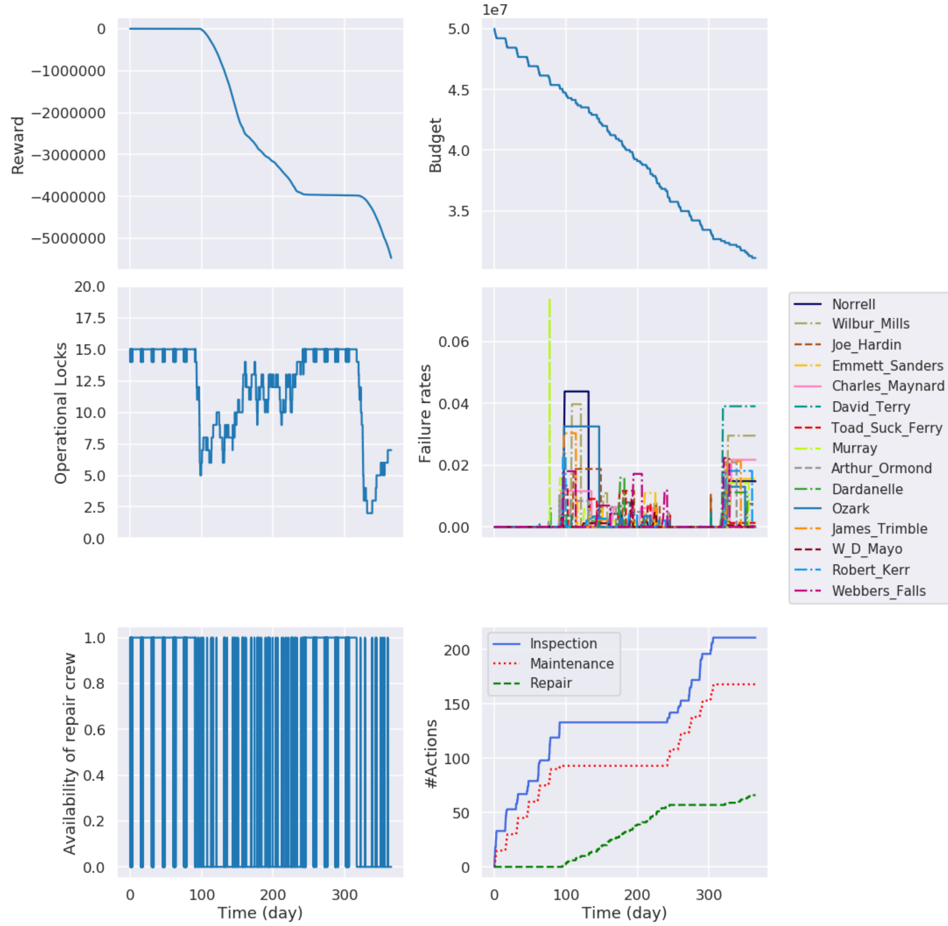

Figure 4: Performance measures over the planning horizon.

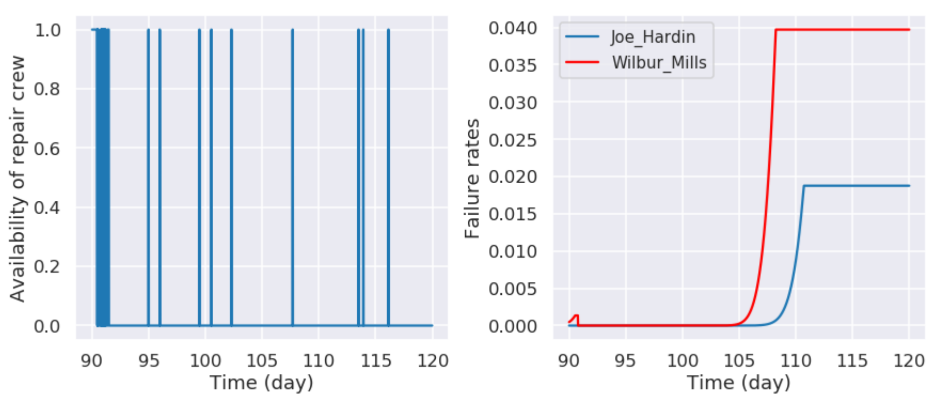

Figure 5: A closer look at the crew availability and failure rates of two locks in a month.

alternative for solving the optimal maintenance planning problem involving a series of actions. The case study on the Mississippi River system and MKARNS shows that a well-scheduled series of actions will significantly improve the locks' availability and thus the throughput of the entire system. In our future research, more advanced

Table 4: Initial budget vs. crew actions (mean values from 10 replications).

Initial budget	# inspections	# preventive maintenance	# repairs
$25,000,000	222	227	54
$50,000,000	212	223	56
$75,000,000	205	207	59

Table 5: Initial budget vs. the availability of locks (mean values from 10 replications).

Initial budget	Nor-rell	Wilbur Mills	Joe Hardin	Em-mett Sanders	Charles Maynard	David Terry	Toad Suck Ferry	Mur-ray	Arthur Or-mond	Dard-anelle	Ozark	James Trimble	W D Mayo	Robert Kerr	Web-bers Falls
$25,000,000	81%	82%	80%	83%	83%	85%	84%	87%	87%	85%	83%	85%	81%	81%	84%
$50,000,000	81%	84%	84%	84%	88%	85%	86%	87%	85%	86%	81%	83%	75%	77%	82%
$75,000,000	83%	83%	81%	82%	82%	85%	82%	85%	85%	85%	82%	82%	78%	79%	83%

maintenance strategies involving multiple maintenance crews and different effects of maintenance actions will be studied. Especially, we will focus on how to effectively deploy repair teams and allocate shared resources to minimize the number of lock failures.

ACKNOWLEDGMENTS

This material is based upon work supported by the U.S. Department of Transportation under Grant Award Number 69A3551747130. The work was conducted through the Maritime Transportation Research and Education Center at the University of Arkansas. The authors also express their gratitude to the funding provided to support this study from the U.S. National Science Foundation EPSCoR RII Track-2 Program under Award number OIA-2119691 and the U.S. National Science Foundation EPSCoR RII Track-1 Program under Award number OIA-1946391.

DISCLAIMER

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