Transportation Consortium of South-Central States

Tran-SET

Solving Emerging Transportation Resiliency, Sustainability, and Economic Challenges through the Use of Innovative Materials and Construction Methods: From Research to Implementation

Deep Reinforcement Learning-based Project Prioritization for Rapid Post-Disaster Recovery of Transportation Infrastructure Systems

Project No. 20PPLSU14

Lead University: Louisiana State University

Collaborative Universities: Texas A&M University

Final Report

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16. Abstract

Among various natural hazards that threaten transportation infrastructure, flooding represents a major hazard in Region 6's states to roadways as it challenges their design, operation, efficiency, and safety. The catastrophic flooding disaster event generally leads to massive obstruction of traffic, direct damage to highway/bridge structures/pavement, and indirect damages to economic activities and regional communities that may cause loss of many lives. After disasters strike, reconstruction and maintenance of an enormous number of damaged transportation infrastructure systems require each DOT to take extremely expensive and long-term processes. In addition, planning and organizing post-disaster reconstruction and maintenance projects of transportation infrastructures are extremely challenging for each DOT because they entail a massive number and the broad areas of the projects with various considerable factors and multi-objective issues including social, economic, political, and technical factors. Yet, amazingly, a comprehensive, integrated, data-driven approach for organizing and prioritizing post-disaster transportation reconstruction projects remains elusive. In addition, DOTs in Region 6 still need to improve the current practice and systems to robustly identify and accurately predict the detailed factors and their impacts affecting post-disaster transportation recovery. The main objective of this proposed research is to develop a deep reinforcement learning-based project prioritization system for rapid post-disaster reconstruction and recovery of damaged transportation infrastructure systems. This project also aims to provide a means to facilitate the systematic optimization and prioritization of the post-disaster reconstruction and maintenance plan of transportation infrastructure by focusing on social, economic, and technical aspects. The outcomes from this project would help engineers and decision-makers in Region 6's State DOTs optimize and sequence transportation recovery processes at a regional network level with necessary recovery factors and evaluating its long-term impacts after disasters.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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ACRONYMS, ABBREVIATIONS, AND SYMBOLS

ABM	Agent-Based Model
AHP	Analytical Hierarchy Process
DCC	Direct Construction-related Costs
DOT	Department of Transportation
DOTD	Department of Transportation and Development
DRL	Deep Reinforcement Learning
ICC	Indirect Construction-related Costs
I-O	Input-Output
ISC	Indirect non-construction related Costs
GA	Genetic Algorithm
MHP	Markov Hidden Process
NRP	Network Restoration Problem
NSGA-II	Non-dominated Sorting Genetic Algorithm
OD	Origin-Destination
RL	Reinforcement Learning
SoVI	Social Vulnerability Index
TA	Transportation agency Agent

EXECUTIVE SUMMARY

Catastrophic natural disaster events, including flooding and hurricanes, generally lead to massive obstruction of traffic, direct damage to highway/bridge structures/pavement, and indirect damages to economic activities and regional communities that may cause loss of many lives. The observed consequences from these events make evident their ability to cause largescale damages to society, raising the levels of exposure of all transportation infrastructure. After disasters strike, reconstruction and maintenance of an enormous number of damaged transportation infrastructure systems require each Department of Transportation (DOT) to take extremely expensive and long-term processes. In addition, planning and organizing post-disaster reconstruction and maintenance projects of transportation infrastructures are extremely challenging for each DOT because they entail a massive number and the broad areas of the projects with various considerable factors and multi-objective issues including social, economic, political, and technical factors. Furthermore, decision-makers are supposed to deal with limited federal, state, and local resources in planning the sequential and organized reconstruction of affected transportation systems. In particular, since transportation networks play a pivotal role in disaster recovery of communities as primary routes for salvage, evacuation and restoration, their recovery processes should consider short- and long-term logistics and plan with underlying heterogeneous factors. Yet, amazingly, a comprehensive, integrated, data-driven approach for organizing and prioritizing post-disaster transportation reconstruction projects remains elusive. In addition, DOTs in Region 6 still need to improve the current practice and relevant systems to accurately identify and predict the detailed factors and their corresponding impacts affecting post-disaster transportation recovery.

The main objective of this proposed research is to develop a deep reinforcement learning (DRL)-based project prioritization system for rapid post-disaster reconstruction and recovery of damaged transportation infrastructure systems. This project also aims to provide a means to the Region 6's States to facilitate the systematic optimization and prioritization of the post-disaster reconstruction and maintenance projects of transportation infrastructure systems by focusing on social, economic, and technical aspects. As the critical mass of Region 6's transportation infrastructure has been severely damaged from previous flood and hurricane disasters, this study that concurrently involves the transportation infrastructure systems has a significant impact on the holistic organization and prioritization of Regional 6's transportation systems affected by natural disasters.

With the developed DRL framework for project prioritization, the study evaluated the scenarios of the transportation system recovery with a particular disaster event. The methodology includes the agent-based model (ABM), which consists of two main components: (1) the agent, which is the main decision-maker, and (2) the environment with which the agent interacts. The ABM addresses a simulation scenario with a transportation network affected by a disastrous event that executes necessary recovery projects of transportation systems considering underlying resource limitations (e.g., funds, work crews, materials, etc.). The agent in the simulation is responsible for making a decision and define the priority of the recovery projects. The simulation process is also executed until the end of the full restoration of the transportation network. To identify improved decisions with the accumulated data and experience, this project employed the DRL, which can add the advanced learning ability to the agent. For the learning process, we defined the reward system, which is the function of the following two objectives: (1) the magnitude of the capacity restoration in each time step (which is called state) and (2) the percentage of the in-use resources (this objective shows that the idle resources are minimum, and the agent is working at maximum possible capacity. In each state (time step) of the DRL process, the agent calculates the gained

reward according to the series of action and find the potential reward for future actions. In the training process, the agent does the combination of exploration (simulation with random decisions) and exploitation (simulation based on learnings) and collects the data for all simulations and, after a certain amount of collected data (batch size), uses a deep neural network to execute the learning process. After the learning process, the trained model is able to make the optimal decision based on the dynamics of network restoration in each time step.

The developed DRL-based model contributes to the body of knowledge by providing a new optimization system considering transportation network recovery and minimizing the social impact of the current prolonged recovery process on affected transportation systems and regions. The results show that a new agent-based DRL model produces an optimal recovery plan of damaged transportation systems by considering social, economic, political, and technical factors and analyzing dynamic interaction flows of communities with transportation infrastructure systems before and after disasters occurrence and effects of disaster mitigation and recovery policies on this system. The proposed model explicitly reveals the prioritized logistics of needed recovery projects and the consequences of optimized action policies through agent-based DRL model simulations. This methodology is expected to support public agencies making a risk-based decision for distributing limited resources and systematically arranging disaster recovery projects of transportation systems with the simulations of real-world disaster scenarios. The outcomes of this study are also expected to provide a crucial step toward a comprehensive and informed decision-making process that allows the policy-makers to analyze dynamic but limited resources of transportation system recovery plan, assisting them in having a holistic perspective considering diverse factors of transportation recovery processes and recourses according to socioeconomic factors of affected communities. In addition, this study will lead to more resilient communities and more effective recovery plans, improving social and economic benefits in planning disaster recovery and response processes. Moreover, the expected outcomes from this project would assist not only engineers and decision-makers in the DOTs but also Region 6's State administrators in optimizing and sequencing transportation recovery processes at a regional network level and evaluating their long-term impacts after disasters. Thus, the outcomes generated from this study will be crucial assets for transportation agencies to be a foundation for a comprehensive approach to plan their recovery project and meet the federal regulation of maintaining mobility and safety of the network at an acceptable level as well as fulfilling other objectives including socioeconomic, time, and cost.

1. INTRODUCTION

Increasing disaster events in the last decades have led to billions of dollars of infrastructure losses *(1)* as shown in the recent disaster cases in the United States: Hurricane Katrina in 2005 ($125 billion), Hurricane Sandy in 2012 ($68 billion), 2016 Louisiana flood, Hurricane Harvey in 2017 ($125 billion), Hurricane Irma in 2017 ($65 billion), and Hurricane Maria n 2017 ($92 billion) *(2)*. Infrastructure systems — sometimes referred to as critical infrastructure or lifelines — provide essential services for communities such as energy, water, sanitation, transportation, and communications. Among various natural hazards that threaten transportation infrastructure, flooding and hurricanes represent a major hazard in Region 6's states to roadways as it challenges their design, operation, efficiency, and safety. These catastrophic natural disaster events, including flooding and hurricanes, generally lead to massive obstruction of traffic, direct damage to highway/bridge structures/pavement, and indirect damages to economic activities and regional communities, which may cause loss of many lives. The recent large-scale floods such as the 2017/2018 hurricanes and 2016 Baton Rouge devastating flooding reminded how destructive hurricanes and floods are. The observed consequences from these events make evident their ability to generate largescale damages to society, raising the levels of exposure of all transportation infrastructure. For instance, Hurricane Katrina made landfall on August 29, 2005, providing some of the most plentiful and illustrative empirical evidence of the impact of hurricanes and storm surge on the performance of bridges and the transportation network *(3)*. There is approximately 3,220 km (2,000 mi) of roadway in the Greater New Orleans area which was submerged in floodwaters for up to 5 weeks *(4)*. The overall cost to repair or replace the bridges damaged during the hurricane was estimated at more than $1 billion *(5)*.

Particularly, transportation systems are highly vulnerable to natural hazards and disasters can cause widespread damage to transportation infrastructure, which requires a lengthy and costly recovery process. For example, Hurricane Katrina caused damage to nearly 45 bridges in three states of Alabama, Louisiana, and Mississippi, with repair and reconstruction costs of over $1 billion *(5,6)*. In addition to the recovery cost, the disruption in transportation network services can result in devastating consequences *(7)*. The collapse of a single major bridge also can disrupt traffic flows over a broad region and impede emergency response, evacuation, commuting, freight movement, and economic recovery. For instance, 286 bridges were damaged during the 1991 Northridge earthquake in Los Angeles, California *(8)*, including seven major bridges that collapsed and severely disrupted the serviceability of critical highways *(9)*, causing significant disruptions in the transportation of people and products. Zamichow and Ellis *(10)* also stated that financial losses of affected communities only following the partial closure of Interstate 10, including depressed economy and lost wages, were estimated at $1 million per day. Besides, since the transportation network recovery process typically takes from hours to weeks, months, or even years, the social and economic impact on communities is severely influenced by the multitude of decisions made following a disaster.

After disasters strike, reconstruction and maintenance of an enormous number of damaged transportation infrastructure systems require each DOT to take extremely expensive and long-term processes. In addition, planning and organizing post-disaster reconstruction and maintenance projects of transportation infrastructures are extremely challenging for each DOT because they entail the massive number and the broad areas of the projects with various considerable factors and multi-objective issues including social, economic, political, and technical factors. Furthermore, decision-makers need to deal with limited federal, state, and local resources in planning a sequential and organized reconstruction of affected transportation systems. In particular, since transportation networks play a pivotal role in disaster recovery of communities as primary routes for salvage, evacuation, and restoration, their recovery processes should consider short- and long-term logistics and plan with underlying heterogeneous factors. For instance, after the Louisiana 2016 flooding event, approximately 200 roads closure were reported by the Louisiana Department of Transportation and Development *(11)*, which made the recovery process significantly demanding. This challenging situation reveals the importance of developing a robust strategy for Region 6's transportation agencies to logically optimize and systemically prioritize the reconstruction and maintenance projects of damaged transportation infrastructure systems for short- and long-term periods, not only considering limited funds, time, and resources but also maintaining safety and mobility. The complexity of the problem, multiple stakeholders and actors, various objectives, and constraints also reveal an urgent need for a holistic decision-making framework in this area.

Yet, amazingly, a comprehensive, integrated, data-driven approach for organizing and prioritizing post-disaster transportation reconstruction projects remains elusive. In addition, DOTs in Region 6 need to improve the current practice and system to identify and predict the detailed factors and their impacts affecting post-disaster transportation recovery. In recent years, several studies have been conducted to address this issue, however, they were rarely able to tackle the complexity of the problem due to limitations such as computational constraints. Moreover, the previous studies mainly focused on specific planning of the post-disaster recovery process and rarely covered a comprehensive set of objectives. Utilizing cutting-edge and emerging approaches such as artificial intelligence and agent-based modeling can help decision-makers to overcome these shortcomings for efficiently allocating available reconstruction resources to reduce recovery time and cost while avoiding negative mobility and safety issues as well as post-disaster community impacts. In this regard, this study aims to solve this complex recovery prioritization problem by adopting emerging approaches, artificial intelligence, and agent-based modeling for evaluating recovery priorities of damaged transportation infrastructures and affected regions through a network mobility analysis and resource allocation technique.

2. OBJECTIVES

The main objective of this proposed research is to develop a data-driven reinforcement learning and project prioritization system for rapid post-disaster reconstruction and recovery of damaged transportation infrastructure systems. In other words, this project provides a new prioritization approach for rapid and optimized post-disaster recovery that evaluates recovery priorities of damaged transportation systems through a multi-agent DRL system. This project also aims to provide a means to all Region 6's States to facilitate the systematic optimization and prioritization of the post-disaster reconstruction and maintenance plan of transportation infrastructure systems by focusing on social, economic, and technical aspects. To accomplish the proposed goal, this project examined the factors of transportation recovery projects with the previous flood disasters. In addition, the PIs obtained historical recovery and maintenance data of transportation infrastructure systems and flood-affected transportation systems to design a prioritization process with these critical factors.

The data obtained were utilized for developing an agent-based model and further analyzed by the deep reinforcement learning technique, which is a new feature integrating deep learning and reinforcement learning. In addition, the PIs have developed a multi-agent model incorporating reinforcement learning of transportation recovery simulations to optimize the reconstruction plan. The outcomes of the study are expected to provide a significant impact on assisting not only engineers and decision-makers in Region 6's DOTs in optimizing and sequencing transportation recovery processes at a regional network level and evaluating their long-term impacts after disasters.

3. LITERATURE REVIEW

3.1. The Direct and Indirect Impact of Disasters on Transportation Infrastructure

Catastrophic natural disasters frequently cause widespread destruction to transportation infrastructure and communities. Quantifying the economic impact of disasters on the transportation network is critical in strengthening transportation systems and developing sound policies for network recovery and mitigation. To quantify the economic impacts, one study captured the consequences of a disruption, which is one of the challenging tasks *(12)*. Various studies also explored this topic from different perspectives (e.g., series of reports NCHRP 525 *(13)*). However, their methods and applications are somehow limited to providing comprehensive modeling approaches because of the lack of capabilities in quantifying a complex relationship and associated impact among people, goods movement, and economic activity. While a few models have quantified the direct impacts such as damage of infrastructure and loss of travel time *(14)*, there is relatively little understanding of indirect impacts that can cause a multiplier negative impacts, including a reduction in jobs, property values, and others in the long term. The ability to estimate the short/long term economic impacts using quantitative methodologies and simulation tools requires the integration of engineering, economic, and policy frameworks. Since disruptions of transportation systems have short, medium, and long-run impacts on local, regional and national economies, there is a significant need that warrants their quantification using state-of-the-art tools.

Several empirical studies have been conducted to estimate the economic impacts of disasters *(15-17)*. However, only a few of them focused on measuring the economic impacts of infrastructure disruptions caused by disasters. The Input-Output (I-O) modeling is the most common method to analyze the regional impacts of disruption. The I–O model entailing a solid theoretical foundation in economics is used in the HAZUS loss estimation methodology *(18, 19)*, which is one of the most comprehensive methodologies to estimate the losses of a natural hazard. Kim et al. *(20)* also estimated the direct and indirect economic impacts of disruptions in the regional transport networks caused by an earthquake considering the interindustry relationships through an integrated regional I–O model and network assignment model. Although considerable efforts of these previous studies have been made to assess the physical and economic impacts of a disaster, an explicit social impact analysis necessary for the disaster impact assessment or hazard loss estimation is typically overlooked. This issue is mainly due to the difficulty in quantifying the social impacts of disasters and corresponding infrastructure disruption.

3.2. Social vulnerability and transportation infrastructure disruption

In disaster events, infrastructure disruptions frequently cause or exacerbate diverse types of socioeconomic impacts, including health, social, economic, and environmental consequences. Vulnerability to infrastructure disruption differs from population groups. For disasters in general, several studies *(21-24)* have examined the heightened vulnerability of population groups such as the elderly, children, and low-income households. Various population groups with different socioeconomic statuses entail the different levels of vulnerability in terms of infrastructure disruption and disaster mitigation and response in several ways: population groups may face differential likelihood of experiencing infrastructure disruption in a disaster (i.e., different exposure); they may have differential capacity to withstand such disruption; they may have differential access to emergency assistance to alleviate infrastructure loss; and they may have differential resources to find infrastructure service alternatives. For instance, analysis of the impacts of subway transportation disruption in New York City after Hurricane Sandy indicated that the neighborhoods that were most severely affected by transit disruption differed demographically from those affected by coastal flooding, with the greatest access loss occurring in poor, predominantly Asian and Latino areas *(23)*. Another study about evacuation after flood events found that low-income populations have differential transportation accessibility to shelters and safe zones. In addition, it noted that persons with disabilities are especially dependent upon transportation that can meet their needs; lack of suitable transport is a key factor in their reluctance to evacuate before hurricanes and presents a barrier to post-disaster recovery *(24)*.

3.3. Transportation network and prioritization of recovery projects

Prioritizing post-disaster recovery of transportation infrastructure systems can be mainly considered as the resource-constrained project planning problem. Several research studies examined prioritization techniques for post-disaster repair and reconstruction of damaged transportation infrastructure systems. These studies mainly differ in prioritization criteria, constraints, and methodology. The following section includes the previous research studies related to the transportation network and prioritization of recovery projects.

- Basőz and Kiremidjian *(25)* prioritized urban road bridges without considering the performance of the entire system. The methodology was designed based on the assessment of importance and damage risk evaluation of highways to assist the decision-making for pre-earthquake mitigation strategies, emergency response planning, and management activities.
- Cagnan and Davidson *(26, 27)* presented a model to retrieve lifelines after an earthquake disaster. This model includes three sub-models: (a) a destruction estimation model, (b) a reconstruction model, and (c) an estimation model for calculating the direct and indirect cost imposed. The output of each sub-model is the input of the next one. Then, it prioritizes the elements for reconstruction planning based on determined scores and the two parameters of destruction level as well as recovery accessibility.
- Chen and Tzeng *(28)* also presented an optimal fuzzy multi-objective model to assist with restoration decisions for a post-quake road network as a reconstruction schedule by utilizing the concept of network restoration problem (NRP) and genetic algorithm (GA). They also addressed an asymmetric traffic assignment technique as a measurement tool for the effectiveness of this restoration schedule. In their work, they developed and applied a modified GA technique in order to overcome the sophistication of the model, which is a combinatorial NP-hard complexity optimization problem.
- A group of authors conducted three studies to optimize the prioritization problem of transportation networks' reconstruction after a disaster. These studies developed an equilibrium algorithm to evaluate the functionality of transportation networks after a disaster *(29)*, an optimization-based solution of reconstruction plans for damaged transportation networks in the post-disaster period *(30)*, and a model to optimize plans of retrofitting damaged transportation networks after a disaster *(31)*.

- Zamanifar and Seyedhosseini *(32)* also developed a Fuzzy VIKOR technique to rank roadway reconstructions after a disaster. They utilized ArcGIS and EMME2 for network and traffic analysis and provided a rating list as an optimized solution.
- Orugbo et al. *(33)* presented a model integrating Analytical Hierarchy Process (AHP) and Reliability Centered Maintenance to generate a prioritization plan of roadways recovery. The researchers categorized failures of roads into four classes by using the reliability logic and its associated risk values. They also used AHP to deal with qualitative variables, analyze decision-making criteria, and break down the road network prioritization plan into easier levels.
- Nifuko *(34)* proposed a stochastic methodology to prioritize highway network recovery projects. The researchers incorporated four criteria of difficulty, importance, urgency, and cost as decision-making parameters into the AHP method to calculate numeric values of factors weights and plan the bridge restoration prioritization.

Although invaluable efforts have been made to optimize the post-disaster recovery process based on the physical and economic impacts of a disaster, an explicit analysis of the underlying community vulnerability and socioeconomic factors is typically absent due to the difficulty in quantifying these factors.

- Oh et al. *(35)* evaluated the criticality of infrastructure systems to prioritize the infrastructures that need attention in case of an emergency. The two main criteria, including vulnerability and intensity assessment, were incorporated into their proposed decision support system. The researchers also investigated the socioeconomic impact of the disaster by analyzing the impact of critical infrastructure on industries and communities in their decision-making process. They used the AHP method to find the relative importance of infrastructures.
- Ghannad and Lee *(36)* presented a post-disaster recovery prioritization approach that evaluates the optimal recovery priorities of damaged transportation infrastructure and affected regions through a resource allocation analysis. The authors integrated the Analytical hierarchy process (AHP) method with the non-dominated sorting genetic algorithm (NSGA-II) approach to incorporate the multi-faceted factors for optimizing the various goals of the post-disaster recovery of the transportation network, including resource limitations and socioeconomic factors of affected communities.

Table 1 presents an organized summary of reviewed previous works, including their prioritization criteria, method, and constraints.

Table1.Summary of previous research studies in prioritization of post-disaster recovery projects

Research study	Methodology		Criteria	Considering socioeconomic factors
	Traffic analysis	Decision-making and optimization		
Basőz and Kiremidjian *(25)*	-	Risk Analysis	- Vulnerability - Importance - Economic/social factors	Yes

Chen and Tzeng *(28)*	Asymmetric traffic assignment	fuzzy multi-objective GA-based model	- Total reconstruction time - Convenience for travelers in a road network during reconstruction - Idle time between any two work troops	No
Orabi et al. *(29)*	User equilibrium assignment	GA	- Reconstruction Cost	No
El-Anwar et al. *(30)*	User equilibrium assignment	Mixed Integer Linear Programming	- Reconstruction Cost - Contractor assignment	No
El-Anwar et al. *(31)*	User equilibrium assignment	Goal Programming Linear-integer programming	- Reconstruction Cost - Contractor assignment - Computational cost	No
Nifuko *(34)*	-	AHP	- Difficulty - Importance - urgency - cost	No
Orugbo et al. *(33)*	-	AHP-Reliability Centered Maintenance	- Reliability	No
Zamanifar and Seyedhosseini (32)	EMME2 software	Fuzzy VIKOR	- Route importance - Damage level	No
Oh et al. *(35)*	-	AHP	- vulnerability - intensity	Yes
Ghannad and Lee *(36)*	-	AHP-GA	- Time - Cost - Socioeconomic benefits	Yes

3.4. Agent-based deep reinforcement learning

This study applied an agent-based deep reinforcement learning approach to prioritize damaged transportation infrastructure systems after a disaster. An agent is a computer program that reflects the actions of an entity (can be an individual or organization) in the system *(37)*. The agents have several characteristics. First, they are assumed to follow the logical rules. Second, they are interdependent, which means they interact with other agents and influence them in various situations. Third, the agents are adaptive that can replicate or learn (38,39). Intelligent agents can capture the status of the environment and changes around them, take actions that help them to achieve their goals, and, more importantly, learn through their (or others) past experiences *(40)*. As a result, the intelligent agents can represent interactive entities of a system, such as decision-makers in the recovery process. Therefore, the post-disaster recovery process can be modeled as an agent-based system in which one or more intelligent agents behave and interact autonomously on behalf of their users across open and distributed environments to achieve a common goal. Agent-based systems were rarely used within a disaster recovery context, and their capabilities have not been fully exploited in providing a comprehensive, proactive decision-making system that allows decision-makers to optimize the disaster recovery process *(39)*.

With the objective to address optimization-complexity, this study aims to develop a reliable model for disaster recovery of damaged transportation infrastructure that integrates ABM and deep reinforcement learning (DRL). Reinforcement Learning (RL) is a computation approach stemming from the literature on machine learning and artificial intelligence. This method has been used to improve model outcomes by providing numeric reinforcing rewards to those actions in a system that lead towards the achievement of a set of defined objectives *(41)*. In this study, DRL provides a means to incorporate optimization procedures into an ABM that allows the agent to interact with its environment while learning how to improve its decision-making behaviors. The authors adopted the DRL algorithms to evaluate the post-disaster condition and relay information to the agents that describe what and when disaster recovery decisions should take place in order to achieve the optimal post-disaster recovery objectives.

4. METHODOLOGY

4.1. Overview

To develop a foundational framework for transportation project prioritization during disaster recovery, the PIs have integrated ABM and DRL techniques to improve data processing and computing capabilities. ABM has been widely used to model with a collection of decision-making entities as named agents, which support the assessment of current situations and provide diverse decision-making options on the basis of a given scenarios, executing various behaviors. The ABM addresses the simulation scenario with the transportation network affected by a disastrous event. The impact of the damage to the transportation network is reflected by decreasing in-service capacity of specific roads within the network. Thus, the restoration process consists of several projects and the order of their completions that can affect the fact that how the network capacity would be recovered to its pre-disaster condition. The ABM simulation executes the projects scheduling considering the resource limitation (e.g., funds, work crews, materials, etc.). The ABM consist of two main components: (1) the agent, which is the main decision-maker, and (2) the environment with which the agent interacts. The agent in the simulation is responsible for defining the priority of the projects to restore the network to its prior service. To this end, in each time step, the agent makes the decision of starting a new project and its execution mode (normal or accelerated mode) or doing nothing (keep progressing on the active projects). The simulation starts with a random selection of the project at the beginning (time=0), allocating the required resources, and updating the available resources (deducting the in-use resources from total resources). Then the possibility of starting a new project is defined, and if given scenarios have enough resources, another project can be started. These analyses would be repeated in each time step (e.g., day, week, or month).

To reflect the real-world situation and conduct realistic analyses, the PIs have incorporated multiple forms of data obtained from various sources into the model. One of the data types the PIs used is the simulation data from FEMA's Hazus models and maintenance data from LA DOTDs (the Pavement Management System) and the City of Houston (the Pavement condition data), to estimate the extent of damage to the road segments following the flood, as well as traffic data from the transportation network. PMS in each state DOT and city provide a set of data and tools that helps consistent pavement condition assessment and road network administration. This pavement condition data can be evaluated to determine the maintenance and rehabilitation priorities and strategies according to the pavement damage induced from the flooding disaster and pavement deterioration rate. The PIs have utilized the PMS and Pavement Condition data analyses conducted from the previous Tran-SET project (Holistic Network-level Assessment of Pavement Flood Damages, Project No. 19PLSU13). Other data used include network inventory and topological data, socioeconomic data, and financial information from recovery efforts that are directly tied to the extent of the damage.

Road closures and damaged roads caused by the disaster event have an immediate impact on the performance of the transportation network. In addition, each recovery project has one or more completion milestones, and in each milestone, the capacity of the road is recovered by a certain amount. Partial restoration of a single road affects the average travel time of the network. In order to evaluate the immediate impact of the disaster on the transportation network performance as well as the effects of the projects' completion milestones on the restoration of the performance, the PIs adopted a network traffic analysis methodology based on user equilibrium assignment and Frank-

Wolfe-Algorithm *(42)*. The PIs also developed a cost model to incorporate the reconstruction cost in the model and find the optimal prioritization of the recovery projects. Three major costs were considered in the proposed cost model (1) direct construction-related cost representing the resource utilization and project execution costs, (2) indirect construction-related cost expressing the time-dependent costs of projects, and (3) indirect non-construction costs reflecting the socioeconomic impact of disruption in transportation network after a disaster and during the recovery process.

The PIs deployed deep reinforcement learning (DRL), a methodology that combines reinforcement learning and deep learning, to fully capture the dynamics of the transportation network recovery process. The deep Q-network (DQN) learning framework developed by Mnih et al. *(43)* was adopted and applied in the recovery process prioritization. DQN is an integration of a Q-learning algorithm and deep neural network, which shows efficient performance in several domains such as transportation *(44)* and autonomous vehicles *(45)*. In the proposed method, initially, an agent makes a decision randomly and executes the simulation process until the end of the full restoration of the network. However, after a certain simulation runs and collecting the data from the previous experiences, the agent is able to use its experience and make better decisions. This point is when the DRL plays a pivotal role in improving the decision-making process by adding the learning ability to the agent. DRL agent achieves optimal decision by using a defined reward system, which is the function of several objectives, including the magnitude of the capacity restoration in each time step, the percentage of the in-use resources (this objective shows that the idle resources are minimum, and the agent is working at maximum possible capacity.), the final cost and time of the recovery projects.

In the DRL process, in each state (time step), the agent calculates the gained reward according to the series of action and find the potential reward for future actions. In the training process, the agent does the combination of exploration (simulation with random decisions) and exploitation (simulation based on learnings) and collects the data for all simulations and, after a certain amount of collected data (batch size), uses a deep neural network to execute the learning process. After the learning process, the trained model is able to make the optimal decision based on the dynamics of network restoration in each time step.

Figure 1 shows the overview of the proposed methodology and its components. The following subsections explain the research processes and development of the methodology in detail.

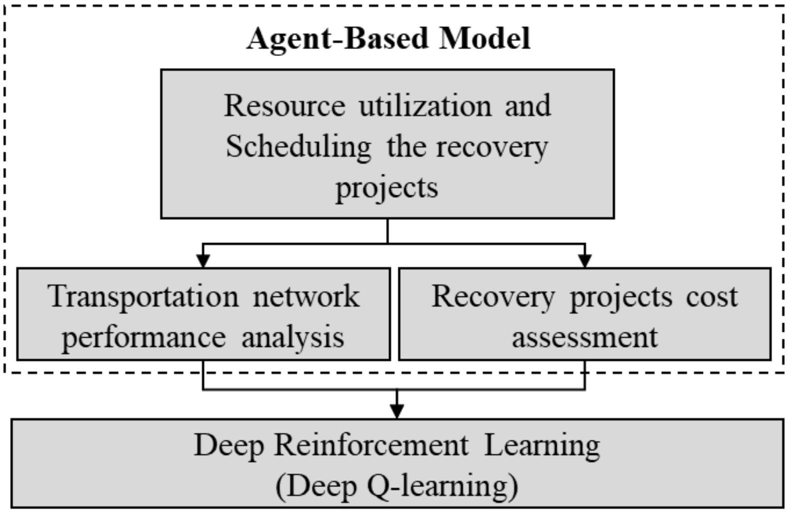

Figure 1. Overview of the methodology

To achieve the given objectives, the methodology was designed in the following five steps: (1) identify relevant factors for post-disaster transportation recovery; (2) adopt social vulnerability assessment tools to quantify and incorporate the vulnerability of communities into the prioritization model; (3) adopt a transportation network performance analysis tool to assess the transportation network performance loss after a disaster and its restoration during recovery process; (4) develop a reconstruction cost model to estimate the various costs of recovery efforts; (5) develop an agent-based deep reinforcement learning model for transportation network recovery.

4.2. Identification of Relevant Factors for Post-disaster Transportation Recovery

In the first steps, the PIs have identified all relevant factors that affect post-disaster transportation recovery processes, including traffic data, post-disaster situations, technical aspects, socioeconomic characteristics, and others according to short- and long-term periods of recovery plans. The criticality of a transportation facility after a disaster can be defined as the function of the hazard severity and imposed damage to the facility, the dependency of a community or an industry on a facility in terms of their daily routine activities, and the social vulnerability of affected people by the damaged facility. A significant amount of data is required to analyze the criticality of the damaged transportation facilities. In this study, the PIs divided the required data into five categories, including hazard-related data, traffic-related data, transportation system data, social information, and economic factors. Using the identified criteria, the PIs investigated the characteristics, decision processes, and priorities of decision-makers involved in transportation disaster recovery.

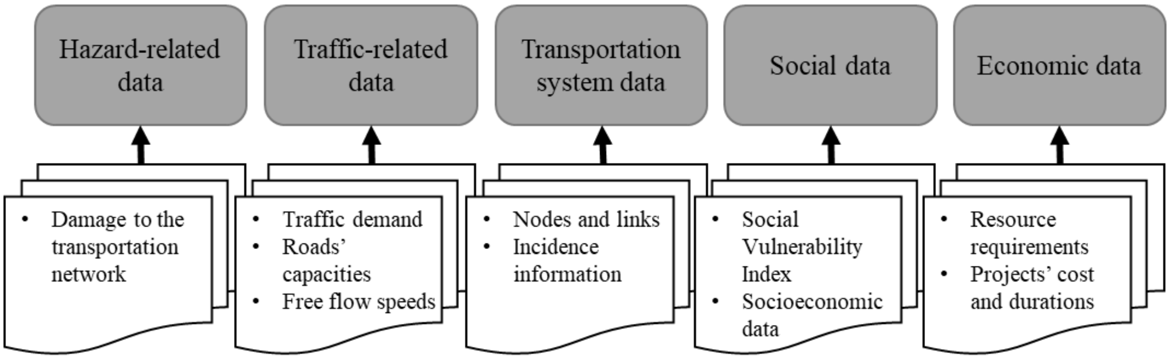

Figure 2. Five types of data collection and analysis for transportation network recovery prioritization

This study utilized the following five main types of data required in the proposed model for performance loss assessment:

1- Hazard-related data

- Damage data to the transportation network components (e.g., roads, bridges, etc.)

The damage level to the transportation network can be evaluated by comparing the maintenance data from DOTs, including the PMS and Pavement Condition data in the pre-disaster condition, with the data obtained from field inspections after the disaster. The PIs have utilized the PMS and Pavement Condition data analyses conducted from the previous Tran-SET project (Holistic Network-level Assessment of Pavement Flood Damages, Project No. 19PLSU13). Previous research studies have shown that the impact of flooding on the roads causes changes in the roughness of the pavement, which is quantified by the International Roughness Index (IRI) on PMS data. It was also revealed that these changes depends on the likelihood of flooding and the degree of loss in modulus of resilience (Mr). Therefore, before-and-after analysis of pavement condition alteration can indicate the level of damage and determine the extent of the required recovery efforts. However, to avoid the lengthy process of damage evaluation by field inspections and PMS data analysis, decision-makers can utilize the FEMA's Hazus models to simulate the disastrous event and estimate the damage level to the transportation network.

2- Traffic data

- A traffic demand that can be described by the origin-destination (OD) pair flows
- A capacity of road segments
- A free-flow speed for each road on a network

The PMS and Pavement Condition data also include the traffic demand data and is used to obtain the Average Daily Traffic (ADT) for each road and calculate the OD demands. For simplicity, the present model assumes that the OD pair flows are static, which indicates that there are no changes in traffic demand on a network during the recovery process.

3- Network topology data

- Nodes that represent demand centers within a network such as intersections, cities, and exits
- Links that represent road segments connecting different nodes
- Incidence information that identifies relationships between nodes and links and a direction of traffic flow on each link

4- Social information

- Social Vulnerability Index which reflects the socioeconomics of affected communities.

The index combines 29 socioeconomic characteristics identified in the literature as contributing to the reduction in a community's ability to plan for, respond to, and recover from hazards *(46)*.

5- Recovery process economic data

- Resource requirements for recovery projects.
- Cost data for execution and resource utilization in the recovery process.
- The duration of reconstruction projects according to selected execution mode
- The schedule of recovery projects and planned recovery milestones

This type of data is generated by the scheduling model and then integrated into the network performance loss model in order to reflect expected impacts of reconstruction projects' progression on recovery of a network performance level.

4.3. Adopting a Social Vulnerability Assessment tool

In this step, the PIs adopted a social vulnerability approach to reflect this factor as one of the critical decision variables in developing the ABM model. One of the well-established vulnerability evaluation models is the social vulnerability index (SoVI), which has been developed by Cutter et al. *(46)* based on specific community socioeconomic data, including household income, median age, median household value, education attained, and percentage of mobile homes. This project utilized the SoVI to qualitatively reflect the socioeconomic status of the communities into the proposed prioritization model.

4.4. Adopting a Transportation Network Performance Model

This model assesses the level of service disruption in a transportation network after a disastrous event and its gradual recovery after the progression in the reconstruction projects. There are several metrics proposed to evaluate the functional performance of the transportation network, such as travel time, direct cost, reliability, distance, and comfort *(47)*. This research study utilized the methodology developed by Orabi et al. *(29)* to evaluate the network performance loss in the model. This methodology utilized the travel time metric because of its importance in affecting travelers on a disrupted transportation network, particularly when they are required to either travel with longer detours or significantly reduce speed on their original routes. Therefore, the additional travel time experienced by users on a damaged transportation network after a disastrous event and during the recovery process represents the magnitude of the network performance loss. Figure 3 schematically represents that how disaster and recovery efforts affect additional total travel time within a damaged transportation network.

The travelers experience maximum additional travel time immediately after a catastrophic event. After starting the recovery process, the additional travel time gradually decreases according to the progress of the planned reconstruction projects, and finally, it diminishes when all reconstruction projects are completed. The additional travel is a flow-dependent metric, so its calculation requires estimating the traffic flow on each link of the network. This calculation is somehow challenging because of inherent difficulties in identifying the travelers' route preferences and the dynamic nature of the recovery process. First, travelers select routes that have the least travel time *(47)*.

Hence, faster routes attract more traffic volume that can exceed their capacities and consequently increase travel time by creating traffic congestions. This behavior and conditions can lead to change in travelers' preferences to consider other alternative routes. Due to these dynamic changes, it is challenging to precisely calculate the volume of traffic on each link of a transportation network, especially when the network is large and includes thousands of links. Second, the complexity of traffic flow estimation is exacerbated by considering the dynamic nature of recovery efforts. As reconstruction projects make progress, the status of damaged roadways can change from closed to partially closed and ultimately open that can dynamically affect traffic flow on the network. This study utilized the user equilibrium assignment and milestone-based network performance assessment to overcome the abovementioned challenges. The details of the transportation network performance loss model used by the travel agency agent is explained explicitly in the following sections.

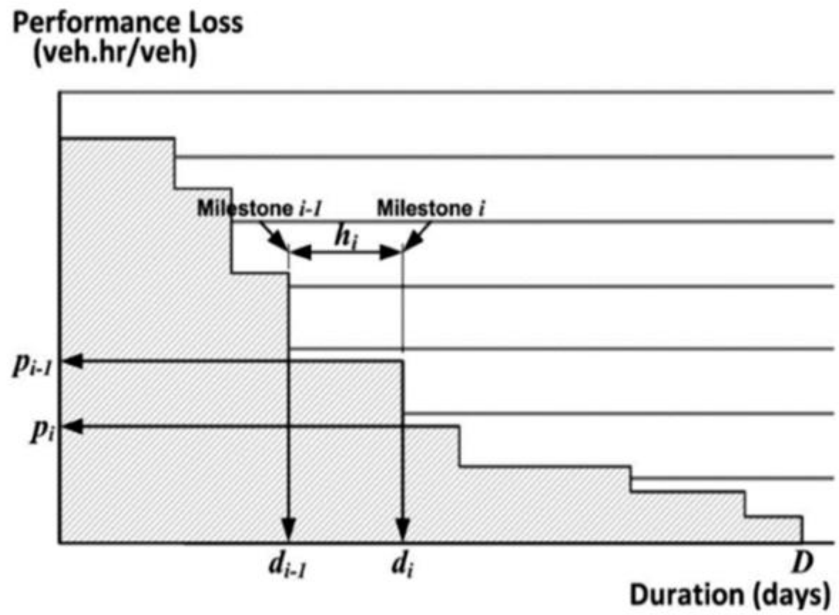

Figure 3. Network performance loss and restoration during the recovery process (source: Orabi et al. *(29)*)

4.4.1. User Equilibrium Assignment

In order to load a traffic demand on a network that reflects the perception of travelers of the fastest routes, the PIs employed the user equilibrium assignment. The user equilibrium assignment is based on Wardrop's first principle, which states that "*no driver can unilaterally reduce his/her travel costs by shifting to another route"* (48). The main goal of this step is to identify the volume of traffic on each link of a transportation network at each recovery milestone. Due to the assumption of a fixed traffic demand during the recovery process, this problem is a deterministic traffic assignment that can be solved by the Frank-Wolfe algorithm. Frank-Wolfe is the effective and widely used algorithm that estimates link flows at equilibrium *(47)*. The PIs followed the steps to execute the Frank-Wolfe algorithm in this study (Figure 4).

1- Define the status of roads at each recovery milestone (i)
2- Find the fastest route with the least travel time for each origin-destination (OD) pair utilizing Dijkstra's algorithm *(49)* according to free-flow speeds on all the open links in a network

3- Load a traffic demand for each OD pair on an associated route with the shortest travel time and calculate an initial set of link flows (v_0)
4- Estimate a travel time on each link by adopting a travel time function ($tt = f(v_{a-1})$) based on a current set of link flows (v_{a-1}) and capacities
5- Use Dijkstra's algorithm to define a new set of shortest paths for each OD pair according to new travel times (tt)
6- Load a traffic demand for each OD pair on a new set of shortest paths (determined in step 5) and calculate a set of auxiliary link flows (v^*)
7- Solve a single objective linear optimization problem (find a value of an averaging multiplier (λ) in Equation 1) to estimate a new current set of link flows (v_a) by averaging

$$(v_{a-1})\text{and } (v^*).\ (v_a) = Min\ f(v_{a-1}\lambda + v^*(1-\lambda)) \quad [1]$$

where:
v_0 = Initial set of link flows;
v_{a-1} = Current set of link flows;
v_a = New current set of link flows;
v^* = Set of auxiliary link flows; and
λ = Averaging multiplier.

8- Check a convergence by using Equation 2. If convergence occurs, (v_a) is a set of link flows at equilibrium at recovery milestone i (v^i) and the algorithm stops; otherwise, counter (a) is incremented by 1, and steps 4 through 7 are repeated until convergence.

$$Max\left[\frac{(v_a - v_{a-1})}{v_{a-1}}\right] < eps \quad [2]$$

where:
eps = denotes a maximum permissible error.

4.4.2. Network Performance Assessment

This phase aims to estimate the overall performance loss of a transportation network after a disaster and its restoration during the recovery process by means of implementing the reconstruction schedule generated by the scheduling model. The following steps are executed to calculate a network performance loss at each recovery milestone:

1- Calculate link flows at equilibrium for recovery milestone i (v^i) using the Frank-Wolfe algorithm
2- Estimate a travel speed on each link (S_l) using Equation 3. A travel speed is a flow-dependent variable that is the function of the link free-flow speed (FS_l), traffic flow on link l at milestone i (v_l^i), and capacity of link (C_l) (TRB 2000).

$$S_l = \frac{FS_l}{1+\alpha(v_l^i/C_l)^\beta} \quad [3]$$

where:
S_l= Travel speed on link l ;

FS_l = Link free-flow speed;
v_l^i = Traffic flow on link l at milestone i; and
α and β = Scalar parameters that depend on the type of the link.

3- Calculate a travel time on each link (tt_l) by dividing its length (len_l) by the speed of traveling on this link (S_l), as shown in Equation 4.

$$tt_l = len_l/S_l \qquad [4]$$

where:
tt_l= Travel time on each link; and
len_l = Length of the link.

4- Estimate the overall travel time for all travelers at equilibrium for recovery milestone i (T^i) using the travel time on each individual link (tt_l), as shown in Equation 5.

$$T^i = \sum_{l=1}^{L} \int_{y=0}^{y=v^i} tt_l(y).dy \qquad [5]$$

where:
T^i= Overall travel time for all travelers at equilibrium for recovery milestone i; and
L = The number of transportation network links.

5- Calculate an additional travel time for all travelers on a network at recovery milestone i (ΔT^i) using Equation 6. The gradual restoration of repaired links in a network over a recovery duration (D) leads to a gradual reduction in an additional travel time (ΔT^i) until full restoration to pre-disaster conditions ($T^{Pre-disaster}$) that will be achieved at the end of the recovery process (Figure 3). Steps 1–4 are repeated for all recovery milestones ($i = 0\ to\ n$).

$$\Delta T^i = T^i - T^{Pre-disaster} \qquad [6]$$

where:
ΔT^i= additional travel time for all travelers on a network at recovery milestone i; and
$T^{Pre-disaster}$ = Overall travel time for pre-disaster conditions.

6- Calculate an achieved performance improvement (in terms of time travel) at milestone i (P^i) using Equation 7. P^i will further be used for calculating a reward associated with the agent's decisions at each state.

$$P^i = T^{i-1} - T^i \qquad [7]$$

where:
P^i= Achieved performance improvement (in terms of time travel) at milestone i.

7- Calculate the overall network performance loss (ΔT) during the recovery process by integrating an additional travel time (ΔT^{i-1}) at different recovery milestones ($i = 1\ to\ n$) that is represented by the area under the curve of (ΔT^{i-1}), as shown in Figure 2. This area under the curve is estimated as shown in Equation 8.

$$\varDelta T = \sum_{i=1}^{n} \Delta T^{i-1}.h_i \quad [8]$$

where:

h_i= The length of time between recovery milestones i and $i-1$

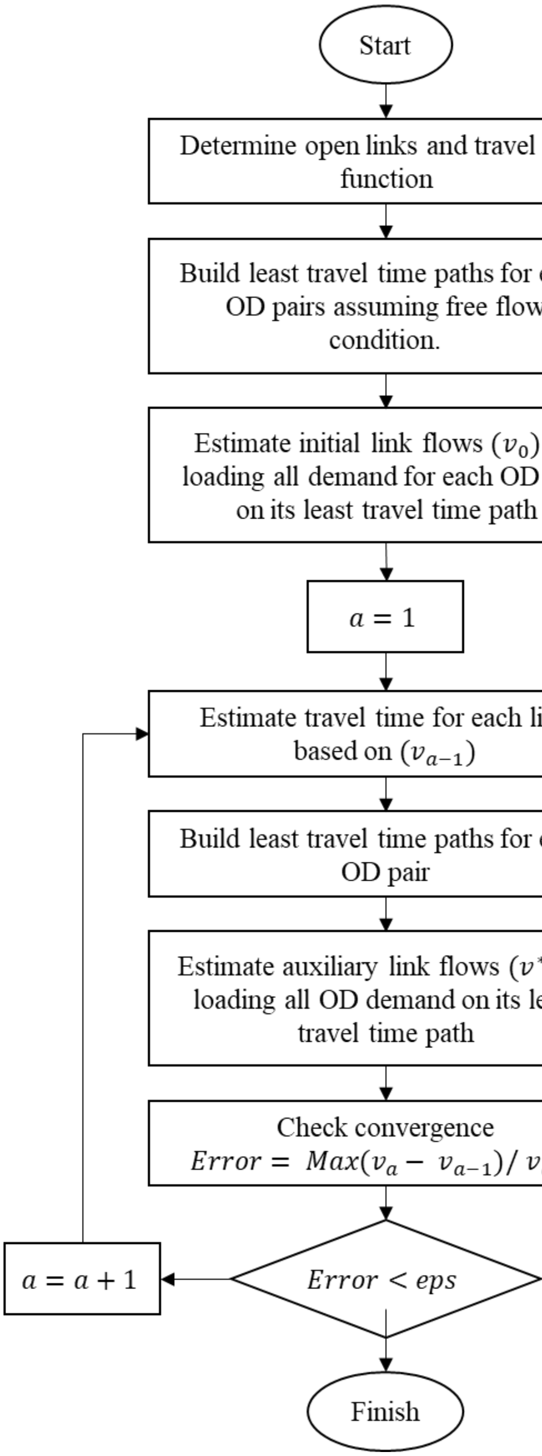

Figure 4. The Frank-Wolfe algorithm process

4.5. Developing a Reconstruction Cost Model

In this step, the PIs developed a reconstruction cost model which aims to quantify the impacts of an agent's scheduling decision on the post-disaster reconstruction cost of damaged transportation networks. In this model, the following three different types of costs were considered: (1) the direct construction-related costs of the recovery efforts (DCC), (2) indirect construction-related costs (ICC), and (3) indirect non-construction related costs (ISC).

The DCC focuses on the costs of reconstruction resources required for all activities in a selected execution mode (Equation 9). Execution of a project in accelerated mode (i.e., overtime policy) reduces the completion time but requires more resources and costs more than normal mode.

$$DCC = \sum_{n=1}^{N} \sum_{x=1}^{X} R_{nm}^{x} dc_r \qquad [9]$$

where:
DCC = Direct construction-related costs of the recovery efforts
R_{nm}^{x} = Resource requirements for activity x of project n in an execution mode of m;
dc_r = The unit cost for resource r;
X = The number of activities; and
N = The number of projects.

The ICC includes time-dependent costs such as site overhead and can be calculated using the duration of each project (d_n) extracted from a recovery schedule and an indirect cost unit rate (ic_n) for a project (Equation 10).

$$ICC = \sum_{n=1}^{N} d_n ic_n \qquad [10]$$

where:
ICC = Indirect construction-related costs
d_n = Duration of project n; and
ic_n = Indirect cost unit rate.

Similarly, the ISC is a time-dependent cost reflecting socioeconomic impacts on road users and business disruption and can be calculated using the duration of each project (d_n) extracted from a recovery schedule and a disruption cost unit rate (dc_n) for the project (Equation 11). In order to incorporate social vulnerability into the model, ISC is multiplied by a coefficient (sv_n) that reflects a weighted average social vulnerability of travelers that are supposed to use a link ($\overline{SoVI_n}$) before a disruption (Equation 12).

$$ISC = \sum_{n=1}^{N} d_n dc_n . sv_n \qquad [11]$$

where:
ISC = Indirect socioeconomic costs
dc_n = disruption cost unit rate of project n; and
sv_n = Coefficient of SoVI for users affected by project n.

$$sv_n = 1 - \left[\frac{\overline{SoVI_n} - SoVI_{min}}{SoVI_{max} - SoVI_{min}}\right] \qquad [12]$$

where:

$\overline{SoVI_n}$ = Weighted average social vulnerability of travelers that are supposed to use a link reconstructed by project n;
$SoVI_{min}$ = Minimum SoVI score of the travelers in the region of study; and
$SoVI_{max}$ = Maximum SoVI score of the travelers in the region of study.

4.6. Agent-based Deep Reinforcement Learning Model Development for Transportation Network Recovery

Attempting to solve the post-disaster transportation network recovery prioritization problem using DRL needs formulation of the problem in an agent-based modeling context, specifically, defining the agent, the state space, the action space, and the reward system.

4.6.1. Agent and action space

In the DRL model, the agent is the entity that learns by interacting with the environment. In this study, an agent was defined as the transportation agency agent (TA), which is responsible for restoring the transportation network accessibility to the pre-disaster level. The main objective of this agent is to generate optimal resource utilization plans and recovery schedules based on the limited availability of reconstruction resources. The agent needs to: (1) consider the constraints of resource limitation and for scheduling reconstruction projects of damaged roads; (2) assess network performance loss for damaged roads within transportation networks; and (3) choose an optimal strategy of resource utilization and scheduling to minimize reconstruction cost as well as network performance loss.

A scheduling model has been designed to support the agent for scheduling the reconstruction efforts while maintaining resource constraints. The scheduling model defines the two main decision variables and evaluates their effects on the recovery schedule, availability of resources, and reconstruction costs. These two decision variables are the project start time and the project execution mode, including the normal or overtime (accelerated) policy adopted in each project. Therefore, the decision space is a 2-dimensional tuple where the first element is a subset of {A project to start, Do nothing} and the second element is a subset of execution mode options {0,1,2}. 0 is associated with "Do nothing," 1 and 2 denote the normal and accelerated execution mode, respectively. The available recovery resources are allocated to the competing reconstruction projects according to the specified decision variables and resource limitations. The scheduling model follows a number of assumptions in the decision-making process as follows:

- Projects cannot start with a smaller number of resources than their requirements.
- Projects cannot be interrupted once started.
- Project durations are fixed based on the execution mode adopted for the project.

The main output of this model is a step-by-step scheduling plan for all recovery projects that fulfill the resource availability limitations.

4.6.2. State space and reward system

The state space aims to accurately describe the state of the environment at each simulation step. The state is the observation of the agent from the environment and is utilized to calculate the reward and choose an action. The space state utilized in this research is composed of three vectors, the first one represents the activation status of the recovery projects (0: inactive, 1: active), the second one represents the progression status of the projects in percent, and the third one represents the percentages of resource utilization.

The next element of DRL is the reward system which plays a pivotal role in the learning process. The agent aims to find a state-action policy that maximizes cumulative long-term reward. Defining an efficient reward system is a challenging task which is an active research topic. In this research, the PIs defined a reward system in which the reward value is proportional to the magnitude of the network performance restoration and the percentage of resource utilization. The final cost and time of the recovery projects. The reward value is also inversely proportional to the final recovery time and cost.

4.6.3. Deep Reinforcement Learning (DRL)

According to the general setting demonstrated in Figure 5, agents interact with a given environment. In other words, an agent perceives a state (s_t) of a system at each time step (t) and needs to choose an action (a_t) according to the available options. Actions of all agents result in the transition of an environment to s_{t+1} based on that, an agent receives a reward (r_t). State changes and obtained rewards are assumed to be stochastic variables that have the Markov property. Thus, state transition probabilities and rewards depend only on a state s_t and an action a_t. It is important to note that agents can choose only their action corresponding to s_t and have no control on or prior knowledge of a state s_{t+1} or a possible reward r_t. These quantities can be observed during the training process by interacting with the environment.

The DRL algorithm used in this research is Deep Q-Learning *(43)*, which is developed to find an optimal action-selection policy. This goal is achieved by utilizing the convolutional neural network to approximate the action-value function, which defines the value of each action from a given state. The values represent long-term rewards. Choosing an action with a high value means earning a future reward, although potentially not an immediate reward.

The depth of a deep neural network shows that there is more than one hidden computational layer of neurons which allows developing features of features, transforming low-level features of the data to high-level ones, potentially increasing network performance.

For the learning process, the DQN framework iteratively selects action at a given state (s_t), then collects reward (r_t) and observes the new state (s_{t+1}) and updates the Q-function using the latest experience (Equation 1).

$$\mathrm{Q}_{t+1}(s_t, a_t) = \mathrm{Q}_t(s_t, a_t) + \alpha\,[r_{t+1} + \gamma max_{a \epsilon A} \mathrm{Q}_t(s_{t+1}, a_t) - \mathrm{Q}_t(s_t, a_t)] \qquad [13]$$

where:
s_t = State at time step t;
a_t = Action at time step t;
r_t = Reward at time step t;
A = The action space;
γ = Discount factor; and
α = Learning rate.

One of the main challenges in DRL implementation is the trade-off between exploration and exploitation. Exploratory actions potentially help to learn more, while the exploitative actions try to gain the most reward according to what has been learned so far. To address this challenge, the

PIs implemented decreasing ε-greedy exploration policy. This method is a simple but efficient way that selects a random action (explore) with a probability ε and selects the action with the highest value (exploit) with a probability 1-ε. The value of ε decreases as training epochs (n) progress to the total number of training epochs (N) (Equation 14).

$$\varepsilon_n = 1 - \frac{n}{N} \qquad [14]$$

where:
n = Training epochs; and
N = The total number of training epochs.

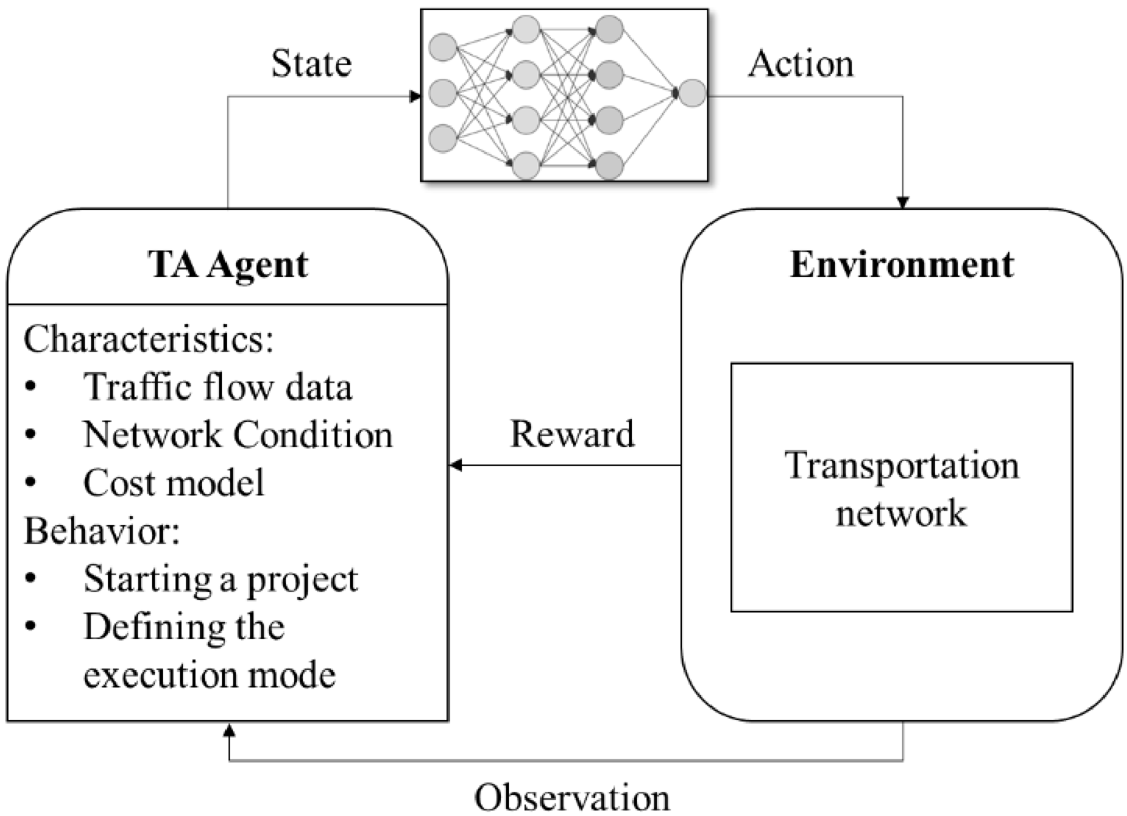

Figure 5. Reconstruction project prioritization agent-based model with deep reinforcement learning model

5. ANALYSIS AND FINDINGS

5.1. Model Assessment

To evaluate the proposed model and demonstrate its application and capabilities in the prioritization of the post-disaster transportation recovery process, the PIs designed and analyzed an illustrative example. The example aims to optimize the reconstruction work for a damaged transportation network after a flooding event in a near real-life setting. To this end, the example was designed based on the simplified real transportation network data of East Baton Rouge Parish, Louisiana, as shown in Figure 6. Figure 7 also shows the simplified topology of the network, including main traffic points (nodes) and the connecting road segments (links). The locations of 6 damaged road segments also are depicted on the network topology in Figure 7. The traffic data, including OD travel demand, free-flow travel time, and link capacities, can be found in Appendix 1. The damage data is hypothetically defined to mimic the potential post-flood damage to the roadways and consequent disruptions. The damage level was assumed in a way that fully closed the damaged road segment and needed recovery efforts to restore its capacity to pre-disaster condition. The presented prioritization problem is a combinatorial optimization problem that is considered NP-hard. This small illustrative example has a solution space with 46080 different solutions ($6! * 2^6$), which is computationally demanding to search all the solution space. To this end, the PIs utilized the proposed methodology to solve and analyze this optimization problem.

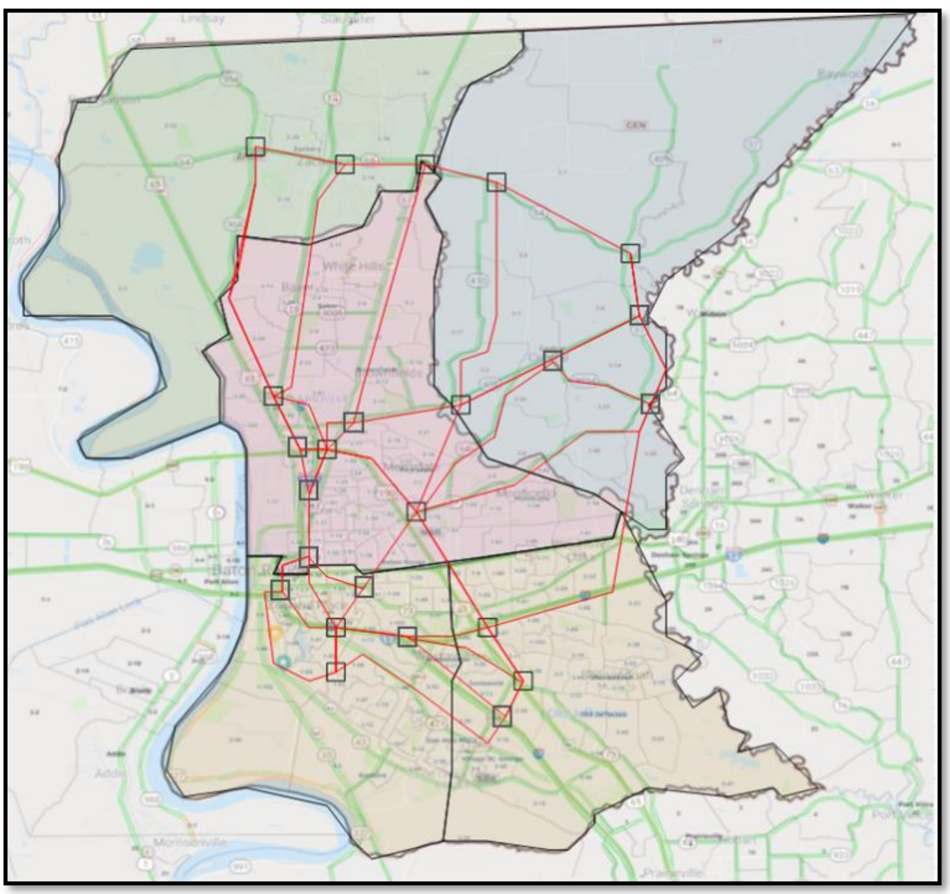

Figure 6. Topology of the damaged transportation network

In this example, the DRL-ABM model is utilized to support identifying two major reconstruction decisions: (1) the recovery projects' start times and (2) the execution modes of the projects. The following data types are also required as the model inputs: (1) the recovery projects data including closed roads and resource requirements, (Table 2), (2) available recovery resources and cost data (Table 3), (3) Socioeconomic information of affected travelers. For simplification, the region of study is divided into five zones with different social vulnerability indices (shown in Figure 6 and Table 4). The SoVI score of each zone is assigned to the travelers from all the origins (Nodes) within that zone.

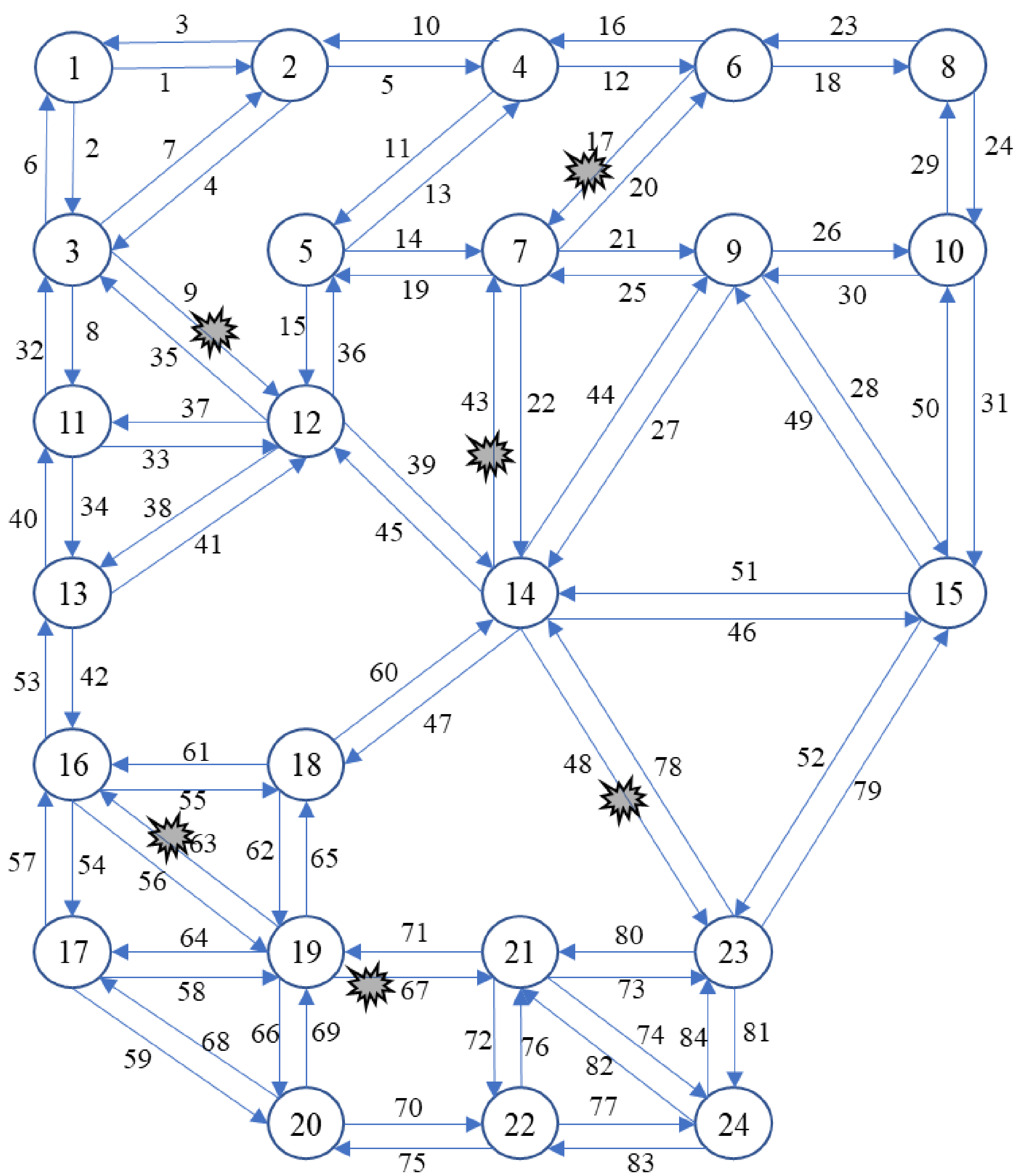

Figure 7. Simplified transportation network and damaged segments

Table 2. Recovery projects data

Recovery projects		Project 1	Project 2	Project 3	Project 4	Project 5	Project 6
ID of closed link		9	17	43	48	63	67
Normal execution mode	Duration	10	12	14	8	14	10
	Resource A	2580	4450	1820	3360	4200	3600
	Resource B	200	350	160	260	310	330
	Resource C	980	2040	1370	1540	1820	1650
Accelerated execution mode	Duration	6	8	8	6	8	6
	Resource A	4730	7000	3350	6720	6300	6600
	Resource B	370	580	290	520	465	605
	Resource C	2160	3400	2510	3080	2730	3025

Table 3. Resource availability and cost data

Resources	Availability (unit)	Cost ($/unit)
Resource A	7000	260
Resource B	600	760
Resource C	3500	110

Table 4. Socioeconomic information of the region of study

Zone	SoVI
Central	Low
South-West	Medium-Low
South-East	Medium
North-West	Medium-High
North-East	High

The above input data was used to analyze a number of scenarios with the proposed DRL-ABM method for (1) evaluate the performance of the model in learning the optimal strategy for maximizing the achieved reward, (2) analyze the effects of various factors such as reward system components and objectives on the outputs of the model. The results of the model assessment and analyses are presented in the following section.

5.2. Results and Discussion

In the first step the PIs, conducted a traffic analysis before and after the disastrous event to calculate the transportation network performance loss. The result of the analysis showed that the travel time per day was increased by 1.3962 (veh.hr/veh) after road closures due to the damaged roadways within the transportation network. In the next step, the PIs trained the agent-based DRL model for prioritization of the recovery projects. The proposed model was implemented in Python programming language and was trained for 1000 epochs. The performance of the agent in achieving reward during the learning process is shown in Figure 8. The agent performance with respect to the traffic metric of average additional travel time per day is depicted in Figure 9. Figure 10 shows the performance of the agent during the training process with respect to the other major metric in the reward system, which is resource utilization percentage. In all three figures, it can be observed that in the initial part of the training process has relatively high variance. This is true because initially, the agent is predominantly taking random actions (exploration). In this part of the training the agent is trying to learn the action-value function. Because of the agent's actions, the recovery process cannot restore the network performance to a satisfactory level, also the resource utilization has a low rate which shows that the agent is not able to use the available resources efficiently to restore the network. As the learning progress, the agent gradually learns the action-value function and starts taking exploitative actions instead of exploratory ones. Decreasing the exploration rate can be observed in all 3 Figures that shows higher reward, better resource utilization and fasted recovery of the network performance.

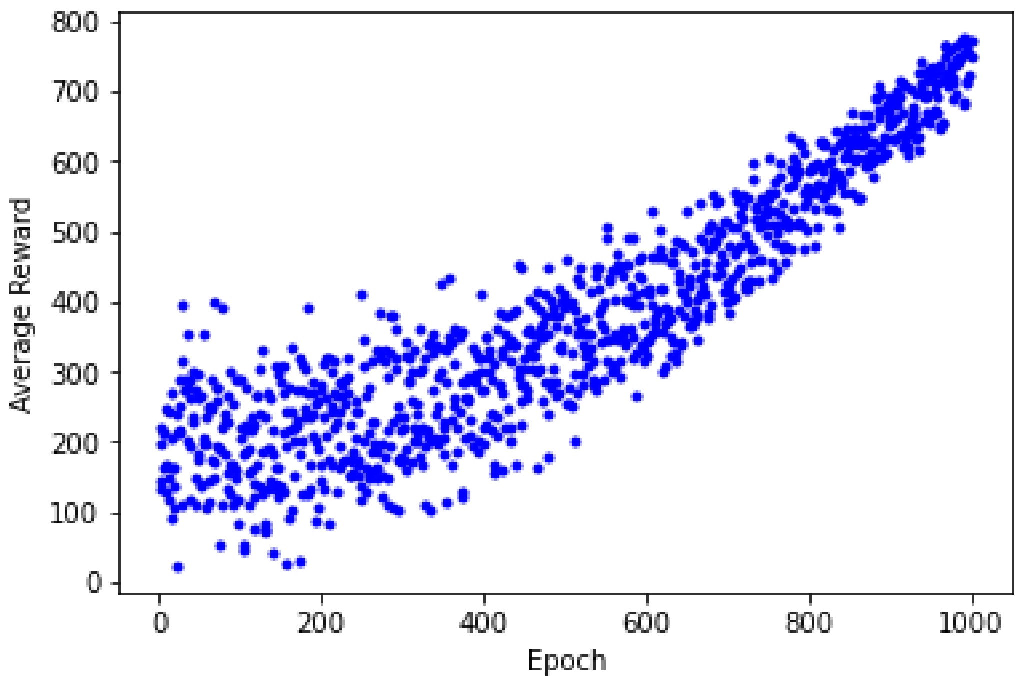

Figure 8. The agent performance with respect to average gained rewards

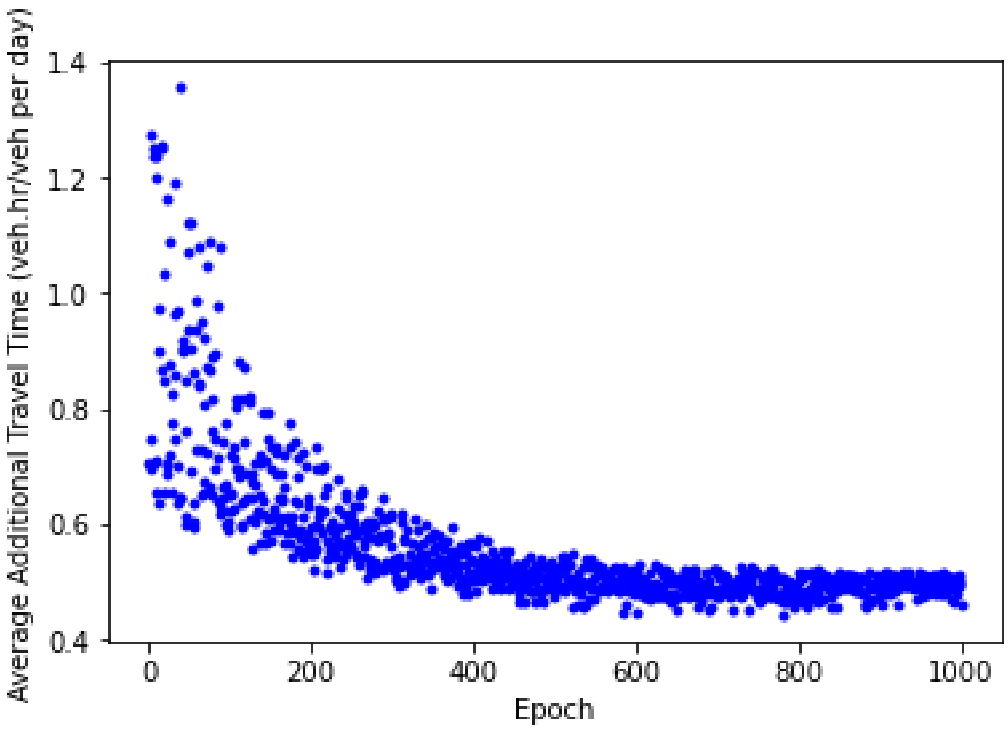

Figure 9. The agent performance with respect to average additional travel time per day

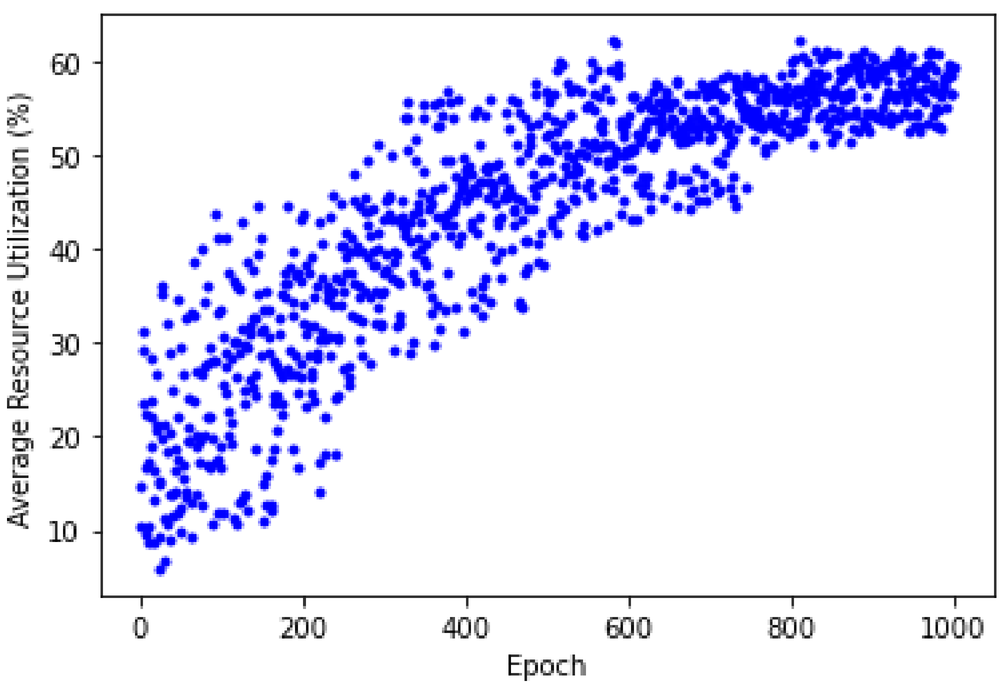

Figure 10. The agent performance with respect to resource utilization percentage

Comparison of Figure 9 and Figure 10 as the two major metrics used in the reward system indicates that the performance of the agent regarding the average additional travel time has a clearer convergence than the resource utilization metric. Although the average resource utilization increases while training, the agent performance has a high variance on this metric even in the exploitative phase. One of the reasons for this issue can be the dynamic characteristic of the resource utilization and existence of multiple resources, which make it challenging to fully utilize the available capacity of resources.

Table 5 shows 7 optimal solutions that were frequently developed by the agent in the exploitative phase. Solution 1 represents the solutions that the agent achieved the highest award according to the defined reward system. This solution is the main output of the agent that considers the reward system as a pre-defined combination of the recovery process objectives. Solution numbers 2, 3, 4, and 5 are the optimal solutions achieved by the agent with respect to the major components of the reward system, including total recovery duration, total recovery cost, resource utilization percentage, and additional travel time, respectively. Although solutions number 2, 3, 4, and 5 outperform solution number 1 in at least one of the objectives, however, solution number 1 provides a more balanced solution for the recovery process. Achieving an optimal solution in the proposed agent-based DRL model highly depends on the design of the reward systems, which should be accurately calibrated according to the preferences of decision-makers. Choosing an appropriate reward for a given task is an ongoing research topic in DRL literature. In DRL, the agent learns in an unsupervised manner, and it would be ideal if the agent would be capable of choosing its own reward system rather than depending on experts to define it, which therefore is the goal of many active researchers. Solutions number 6, 7, and 8 are the solutions with the least sub-components of the cost model, including construction-related direct cost, construction-related indirect cost, and non-construction indirect cost of the recovery process, respectively.

Solution number 5 optimizes the recovery process in terms of accelerating the restoration of the network performance, however, it obviously requires more expenditures. There is a trade-off between minimizing the recovery costs and minimizing the network performance loss and total recovery duration. The acceleration of the recovery process can be accomplished by allocating more resources and overtime working hours, which are associated with lower productivity and higher costs. On the other hand, solution number 6 is an optimal solution with minimum reconstruction direct cost. However, it compromises the recovery duration (40 weeks in comparison with 32 weeks). Solution number 7 is associated with the scenario that intends to minimize the construction-related costs. In this scenario, the agent, regardless of the network recovery process, tried to minimize the completion time of each project by executing them in accelerated mode. So, this scenario has a higher total recovery time as well as a higher total recovery cost.

Table 5. Optimal solutions generated by the agent

Solution	Priorities	Execution Mode	Start time	Completion Time	Total Recovery Time (Week)	Total Recovery Cost ($)	Average Resource Utilization (%)
Solution 1	{P6, P4, P3, P5, P1, P2}	{N, N, A, N, N, A}	{0, 0, 10, 18, 12, 26}	{10, 12, 18, 26, 26, 32}	32	9312,450	88.31
Solution 2	{P4, P6, P3, P5, P1, P2}	{N, N, A, N, N, A}	{0, 0, 10, 18, 12, 26}	{10, 12, 18, 26, 26, 32}	32	9,476,280	88.69
Solution 3	{P4, P2, P3, P6, P1, P5}	{N, N, A, N, N, A}	{0, 17, 1, 9, 10, 29}	{10, 29, 9, 17, 24, 35}	35	9,073,080	80.35
Solution 4	{P2, P6, P3, P4, P1, P5}	{A, N, A, N, N, N}	{0, 6, 6, 14, 18, 22}	{6, 18, 14, 22, 32, 32}	32	9,457,700	89.27
Solution 5	{P4, P3, P1, P2, P5, P6}	{N, A, N, N, A, N}	{0, 0, 8, 10, 28, 18}	{10, 8, 22, 18, 36, 28}	36	9,709,580	78.74

Solution 6	{P2, P4, P1, P6, P3, P5}	{A, N, N, N, N, A}	{0, 6, 6, 18, 20, 34}	{6, 18, 20, 26, 34, 40}	40	9,518,330	68.45
Solution 7	{P2, P1, P3, P4, P5, P6}	{A, A, A, A, A, A}	{0, 6, 14, 22, 28, 36}	{6, 14, 22, 28, 36, 42}	42	10,412,090	74.08
Solution 8	{P4, P2, P3, P6, P1, P5}	{N, N, A, N, N, A}	{0, 17, 1, 9, 10, 29}	{10, 29, 9, 17, 24, 35}	35	9,073,080	80.35

One of the main contributions of this study is incorporating a transportation network analysis algorithm into the model to reflect the dynamic effects of recovery process on transportation network. Figure 11 shows how different solutions in Table 5 differ from each other in restoring the network performance. The gray line represents the solution number 5 with the shortest additional travel time. This acceleration can be achieved with efficient resource allocation and project prioritization.

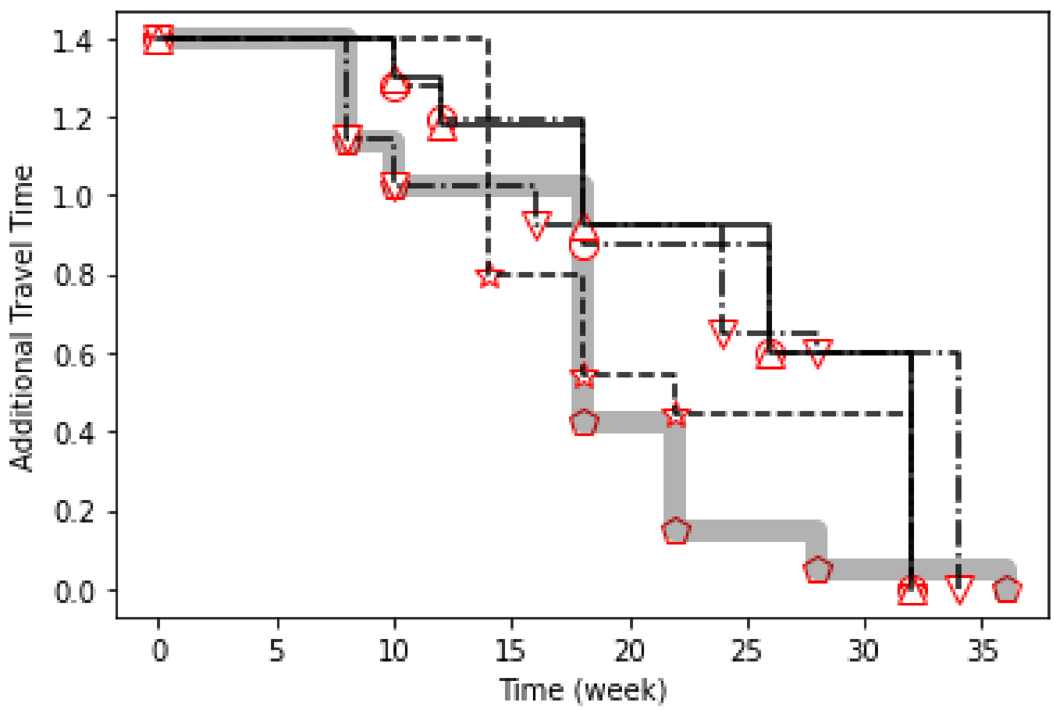

Figure 11. Network performance restoration

In order to evaluate the efficiency of the proposed agent-based DRL model, the Authors analyzed the outputs against the entire space solution. To this end, all possible prioritization scenarios were analyzed to find the global optimal solutions. The results of this analysis are depicted in Figure 12. The abovementioned four objective functions were calculated for all the prioritization scenarios and plotted on six different 2-dimensional diagrams. The seven optimal solutions in Table 5 are also shown in Figure 12 for visual comparison. It can be observed that the optimal solutions generated by the agent, specifically solution 1, reflect one of the near-global optimal solutions of the prioritization problem, which confirms the efficiency of the proposed model in solving the illustrative example and finding optimal recovery strategies.

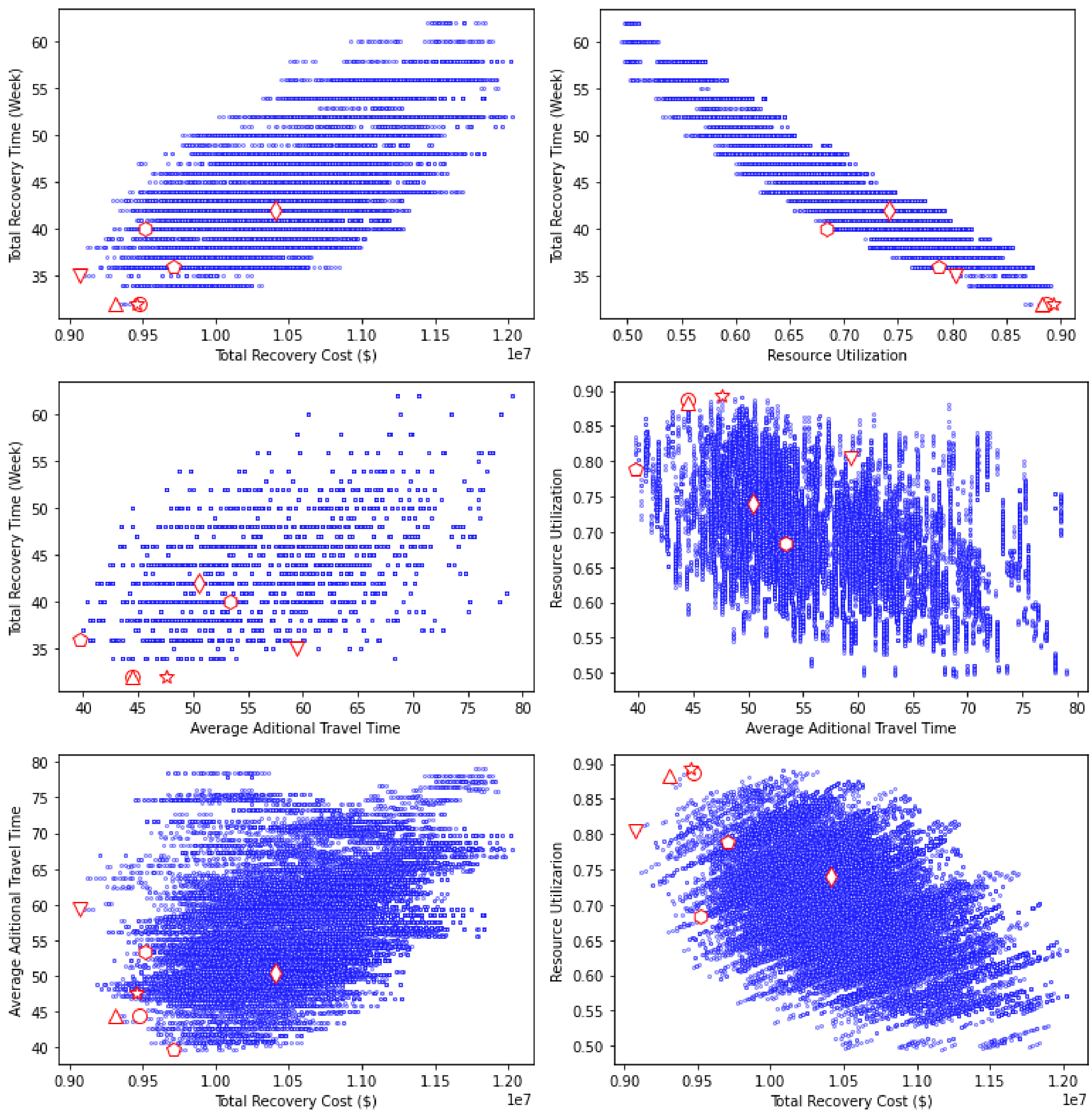

Figure 12. Comparison of generated optimal solutions against the entire solution space

7. CONCLUSIONS

The research focus area of the proposed study is developing and implementing a deep reinforcement learning technique for prioritizing post-disaster transportation systems for enhancing the durability and service life of transportation infrastructure in metropolitan and rural areas. Timely rehabilitation and quick post-disaster recovery of transportation infrastructures play a critical role in the social well-being and economic development of affected regions. This study tackles a crucial topic for optimizing the reconstruction project plans by using emerging prioritization methodologies and data-driven reinforcement learning. This research addresses an impending national interest in transportation infrastructure reconstruction and maintenance after catastrophic disasters. In particular, the proposed research area closely aligns with the mission of the Center that pursues the two following objectives: (1) Objective 2: Promote sustainability and resiliency of the transportation infrastructure renewal and upgrade; and (2) Objective 5: Enhance the resiliency of the transportation infrastructure in the event of extreme weather events. In addition, this problem statement is accurately aligned with Tran-SET's Vision and Mission, which aims to improve the transportation infrastructure through the development, evaluation, and implementation of cutting-edge technologies and innovative construction management processes. If successful, this study will greatly facilitate the planning for rehabilitation projects with minimum effects on mobility, which corresponds with the Tran-SET's research objective of developing cost-effective solutions for the construction and maintenance of the transportation infrastructure in metropolitan and rural areas.

This study proposed a new agent-based reinforcement learning model to examine dynamic interaction flows of communities with transportation infrastructure systems in case of disaster events. The goal of the research is to investigate the effects of disaster mitigation and recovery policies on this system. To achieve these objectives, the authors developed the research methodology in five steps adopting SoVI, ABM, and RL approaches and validating the model with the four different scenarios. The RL-ABM simulation model was tested on a semi-hypothetical example focusing on the five different regions of East Baton Rouge Parish located in Louisiana. The model assessment provided reliable simulation outcomes, which led the authors to confirm the proposed model's reliability and feasibility. Thus, the authors believe that the proposed model helps achieve a shorter recovery time for all sectors and generates an optimal policy to restore the more vulnerable communities by allocating the recovery resources based on socioeconomic characteristics. The outcome of this study is also expected to be an initial step toward a comprehensive decision-making framework that allows the policy-makers to analyze the dynamic behavior of their actions and optimize their decisions which leads to more resilient communities and more effective recovery plans in terms of social and economic benefits. Since several state emergency department possesses high-level disaster mitigation and recovery plan that do not cover dynamic interactions and complicated impacts during a natural disaster, this DRL-ABM model would be a baseline for them to establish a concrete disaster recovery plan reflecting multi-objectives and multi-agent behavior with socioeconomic aspects. Moreover, this approach will enable further comprehensive understanding and multidisciplinary research on the factors affecting the communities' recovery activities.

In terms of the identified limitation of the proposed approach, this model conducted the simplification of all variables varying between 0 and 1 to facilitate using first-order algebraic equations to formulate the model. Formulating the model with metric units would provide more realistic results; however, it is a time-consuming and demanding task because of the scope of the model. However, the numerical labeling and embedding of necessary variables can be flexibly updated with realistic metrics according to given disaster scenarios, agent characteristics, and others. The proposed DRL-ABM also focused on modeling transportation infrastructure; thus, a decision-maker would need to do recovery planning by considering the infrastructure interdependencies and their impact on communities. As a next step, the authors will integrate other available vulnerability dimensions into this proposed model to provide an accurate picture of the host community's sustainable recovery processes.

This study addresses urgent Region 6 states' and national challenges by providing immediately applicable solutions for optimizing and prioritizing post-disaster transportation reconstruction and recovery processes. This project will provide LaDOTD and TxDOT with a guidebook that clearly describes systematic procedures for (1) identifying critical factors of post-disaster recovery of transportation networks, (2) establishing reinforcement learning-based systems accurately analyzing a huge amount of Region 6's States' transportation and disaster data including hourly traffic data, inspection data, pavement management data, and others, (3) revealing new knowledge using the AI-based systems such as traffic flow prediction, disaster-vulnerable transportation segment identification, and infrastructure criticality evaluation, and (4) facilitating project prioritization from the new perspective using socioeconomic, mobility, and safety factors. The research outcomes are therefore expected to bring new scientific knowledge on the implications of systematic resource optimization and AI-based project prioritization of damaged transportation infrastructure. In addition, the intellectual merit of this research study includes a holistic investigation into a network-level post-disaster recovery approach of broadly spread transportation systems for unveiling latent factors and their impacts and quantifying their accurate benefits and weaknesses of various prioritization scenarios. Thus, this system will be new formalized scientific knowledge that will be helpful for practitioners and following researchers by providing a decision-making framework to develop an optimal transportation reconstruction strategy for post-disaster recovery. If not performed, when catastrophic events occur in the future, no methods and tools will exist that can organize limited resources and prioritize short- and long-term reconstruction and maintenance processes for rehabilitating affected transportation infrastructure.

This research team will help practitioners and decision-makers in Region 6's States implement simulation and pilot studies regarding optimizing and prioritizing the post-disaster transportation infrastructure reconstruction and maintenance projects according to historical disaster scenarios. The detailed analysis, evaluation, and implementation guidebook with the middleware software will be provided at the end of the project phase. Since the Hazus flood model is updated by FEMA pertaining to a future disaster event or by a user according to a user-defined potential disaster scenario, this framework will allow State practitioners to quickly and iteratively analyze historical disaster scenarios and execute affected transportation recovery processes for short- and long-term periods. If successful, this project would establish the first view and systematic post-disaster recovery projects of a massive number of damaged transportation systems that practitioners in DOTs can use to prioritize and predict rehabilitation practices. Moreover, this project helps make a well-guided decision on the integrated transportation damage recovery and facilitates a synergetic effort to leverage the uses of the current disaster management practices of Louisiana and Texas.

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APPENDIX 1

Table 6. OD daily travel demand

NODE	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	200	300	500	800	500	1300	500	200	500	300	500	500	400	100	300	300	100	400	300	100
2	100	400	200	400	200	600	200	100	300	100	100	400	200	0	100	100	0	100	0	0
3	100	300	100	200	100	300	300	200	100	100	100	200	100	0	0	0	0	100	100	0
4	500	400	400	700	700	1200	1400	600	600	500	500	800	500	100	200	300	200	400	500	200
5	0	200	200	500	800	1000	500	200	200	100	200	500	200	0	100	100	100	200	100	0
6	200	0	400	800	400	800	400	200	200	100	200	900	500	100	200	300	100	200	100	100
7	200	400	0	1000	600	1900	500	700	400	200	500	1400	1000	200	400	500	200	500	200	100
8	500	800	1000	0	800	1600	800	600	600	400	600	2200	1400	300	700	900	400	500	300	200
9	800	400	600	800	0	2800	1400	600	600	600	900	1400	900	200	400	600	300	700	500	200
10	1000	800	1900	1600	2800	0	4000	2000	1900	2100	4000	4400	3900	700	1800	2500	1200	2600	1800	800
11	500	400	500	800	1400	3900	0	1400	1000	1600	1400	1400	1000	100	400	600	400	1100	1300	600
12	200	200	700	600	600	2000	1400	0	1300	700	700	700	600	200	300	400	300	700	700	500
13	200	200	400	600	600	1900	1000	1300	0	600	700	600	500	100	300	600	600	1300	800	800
14	100	100	200	400	600	2100	1600	700	600	0	1300	700	700	100	300	500	400	1200	1100	400
15	200	200	500	600	1000	4000	1400	700	700	1300	0	1200	1500	200	800	1100	800	2600	1000	400
16	500	900	1400	2200	1400	4400	1400	700	600	700	1200	0	2800	500	1300	1600	600	1200	500	300
17	200	500	1000	1400	900	3900	1000	600	500	700	1500	2800	0	600	1700	1700	600	1700	600	300
18	0	100	200	300	200	700	200	200	100	100	200	500	600	0	300	400	100	300	100	0
19	100	200	400	700	400	1800	400	300	300	300	800	1300	1700	300	0	1200	400	1200	300	100
20	100	300	500	900	600	2500	600	500	600	500	1100	1600	1700	400	1200	0	1200	2400	700	400
21	100	100	200	400	300	1200	400	300	600	400	800	600	600	100	400	1200	0	1800	700	500
22	200	200	500	500	700	2600	1100	700	1300	1200	2600	1200	1700	300	1200	2400	1800	0	2100	1100
23	100	100	200	300	500	1800	1300	700	800	1100	1000	500	600	100	300	700	700	2100	0	700
24	0	100	100	200	200	800	600	500	700	400	400	300	300	0	100	400	500	1100	700	0

Table 7. Transportation network traffic data

Link ID	Free flow travel time	Capacity	Link ID	Free flow travel time	Capacity	Link ID	Free flow travel time	Capacity	Link ID	Free flow travel time	Capacity
1	6	25900.2	22	5	5045.823	43	6	13512	64	6	5059.912
2	4	23403.47	23	5	10000	44	5	5127.526	65	2	5229.91
3	6	25900.2	24	10	5050.193	45	3	14564.75	66	3	4885.358
4	5	4958.181	25	3	13915.79	46	3	9599.181	67	3	9599.181
5	4	23403.47	26	3	13915.79	47	5	5045.823	68	5	5075.697
6	4	17110.52	27	5	10000	48	4	4854.918	69	2	5229.91
7	4	23403.47	28	6	13512	49	2	5229.91	70	4	5000
8	4	17110.52	29	4	4854.918	50	3	19679.9	71	4	4924.791
9	2	17782.79	30	8	4993.511	51	8	4993.511	72	4	5000
10	6	4908.827	31	6	4908.827	52	2	5229.91	73	2	5078.508
11	2	17782.79	32	5	10000	53	2	4823.951	74	4	5091.256
12	4	4947.995	33	6	4908.827	54	2	23403.47	75	3	4885.358
13	5	10000	34	4	4876.508	55	3	19679.9	76	2	5078.508
14	5	4958.181	35	4	23403.47	56	4	23403.47	77	2	5229.91
15	4	4947.995	36	6	4908.827	57	3	14564.75	78	3	4885.358
16	2	4898.588	37	3	25900.2	58	2	4823.951	79	3	5000
17	3	7841.811	38	3	25900.2	59	4	5002.608	80	5	5075.697
18	2	23403.47	39	4	5091.256	60	4	23403.47	81	2	5229.91
19	2	4898.588	40	4	4876.508	61	4	5002.608	82	4	5000
20	3	7841.811	41	5	5127.526	62	6	5059.912	83	4	5000
21	10	5050.193	42	4	4924.791	63	5	5075.697	84	4	5000