Prioritizing Postdisaster Recovery of Transportation Infrastructure Systems Using Multiagent Reinforcement Learning

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Abstract: Postdisaster reconstruction of transportation infrastructures generally entails complex and multiobjective planning and implementation options under uncertainty because of a large number of underlying subjective and objective factors, including social, economic, political, and technical aspects. With limited federal, state, and local resources, it is also challenging for decision-makers to establish a meticulous plan for postdisaster transportation recovery. However, previous studies mainly dealt with the specific planning or execution part of the postdisaster recovery process and rarely considered a comprehensive set of objectives in their investigations. This paper aims to develop a new prioritization approach for rapid and optimized postdisaster recovery that evaluates recovery priorities of damaged transportation infrastructure systems and affected regions through a multiagent system using a reinforcement learning technique. The proposed model contributes to the body of knowledge by providing a new optimization framework, considering transportation network recovery, and minimizing the social impact of the current prolonged recovery process on affected communities. This new methodology is expected to help public agencies make an informed decision for distributing given resources and structurally arranging disaster recovery processes of transportation systems by simulating real-world high-dimensional disaster scenarios and optimizing their recovery plans. In particular, the proposed approach pursues to assist disaster-relevant practitioners in considering a holistic perspective for comprehensive decision-making, incorporating diverse factors of planning transportation recovery and assigning their resources according to socioeconomic factors of affected communities. **DOI: 10.1061/(ASCE)ME.1943-5479.0000868.**

Introduction

Transportation systems are critical in disaster response and recovery, but they are highly vulnerable to natural hazard events, such as earthquakes, hurricanes, tsunamis, and wildfires. Natural disasters can cause widespread destruction of transportation infrastructure systems and communities, frequently leading to lengthy and costly recovery with high direct and indirect costs that can put a massive burden on the economy. For example, the inspection reports and bid estimates indicated that it would cost over $1 billion to repair or reconstruct the nearly 45 damaged bridges (in Alabama, Louisiana, and Mississippi) by Hurricane Katrina (DesRoches 2006; Padgett et al. 2008). The severe storm surge in the coastal area also caused massive deposits of debris, which further hindered the response and recovery efforts for weeks. The direct costs for cleaning the debris were estimated at $200 million (DesRoches 2006). Besides, the failure of the transportation infrastructure typically causes substantial socioeconomic disruptions for the public. For instance, 286 bridges were damaged during the 1991 Northridge earthquake in Los Angeles, (Housner and Thiel 1995), including seven major bridges that collapsed and severely disrupted the serviceability of critical highways (Chang and Nojima 2001), causing significant disruptions in the transportation of people and products. Zamichow and Ellis (1994) 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. As another instance, when Hurricane Harvey approached Texas, more than 200 highway locations were closed or flooded (Engineering News-Record 2017), resulting in traffic congestion, delayed evacuation, and increased rescue costs. The efficient and effective restoration of damaged segments of the transportation network to their predisaster conditions is crucial to control and minimize the aforementioned socioeconomic disruptions.

Planning for a recovery process of the transportation network requires a multifaceted consideration of social, economic, political, and technical aspects. It is generally more complicated than planning for a project portfolio because a government official or practitioners in charge of planning transportation system recovery must deal with various constraints, such as the safety and mobility of the network. Federal Highway Administration (FHWA) regulations require all states to develop transportation management strategies and construction zone planning that ensure maintaining the mobility and safety of the network system at acceptable levels (Bae et al. 2017). In postdisaster situations with a large number of damaged transportation systems, such as roads and bridges, it is challenging to organize recovery resources systematically and build a reconstruction plan robustly. For instance, after the Louisiana 2016 flood, approximately 280 road-closures were reported by the Louisiana Department of Transportation and Development (LADOTD 2016), which made their recovery process severely demanding.

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Besides, decision-makers need to organize limited federal, state, and local resources in planning their subsequent and rapid reconstruction. The complexity of the problem involving multiple stakeholders, actors, objectives, and constraints is an urgent issue to be addressed for acquiring a holistic decision-making approach. Furthermore, aggravating spatial and social inequalities in the previous recovery experiences typically have led to unequal recovery and unbalanced development in socially vulnerable areas (Peacock et al. 2014).

The postdisaster recovery also requires a multidisciplinary approach. The current practices of the DOTs and other transportation agencies need to be improved as a systematic, interdisciplinary, and well-established approach that logically prioritizes recovery processes and provides an optimized reconstruction plan. They also need to improve a process allocating available reconstruction resources to appropriate affected regions in order to reduce recovery time and cost while avoiding negative mobility and safety issues as well as postdisaster community impacts—which is the ultimate goal of postdisaster recovery planning (Ghannad et al. 2019).

In recent years, several studies have been conducted to address this postdisaster recovery issue. However, they were rarely able to tackle the complexity of the problem, which requires complicated and heavy-weight computational processing and analytics. 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.

Background and Literature Review

Disasters and the Transportation Infrastructures

A nation's economic vitality and its quality of life highly depend on the transportation network. This dependency has been growing all over the world as regional, national, and international societal interaction and economic activities become more fully integrated and interdependent. Disruptions of these systems can be devastating for communities. In 2005, Hurricane Katrina revealed that poor transportation system performance could remarkably limit the evacuation and recovery efforts (Freckleton et al. 2012). In the aftermath of the 2010 earthquake in Haiti, thousands of people perished because of disruption in the transportation of needed goods and services. Although providing aid with planes began the next day, it is reported that humanitarian groups struggled to get supplies to victims, mainly due to poor roads and debris (Freckleton et al. 2012).

Postdisaster Recovery Planning of Infrastructures

There are several clusters of studies dealing with infrastructures and disaster events, which can be classified into the following two main categories. The first category is the estimate of disaster-related factors of infrastructure systems, such as risk, vulnerability, and resilience, before disaster events (Jenelius and Mattsson 2012; Khademi et al. 2015; Balakrishnan and Zhang 2020). The second category focuses on infrastructure systems after the disaster, such as damage assessments (Brookshire et al. 1997; Schneider and Schauer 2006; Chen et al. 2020), postdisaster operations of infrastructure systems (Choi et al. 2019), postdisaster emergency response (Oh et al. 2013; Dulebenets et al. 2020), and postdisaster recovery and reconstruction planning (midterm and long-term) (Eid and El-Adaway 2017a, b, c; El-Anwar et al. 2016; Ghannad et al. 2020).

Prioritizing postdisaster recovery of transportation infrastructure systems can mainly be considered as the resource-constrained project planning problem, which has been extensively discussed in the literature (Leu and Yang 1999; Senouci and Eldin 2004; Zhang et al. 2006; Sonmez and Gürel 2016). For example, in one of the recent efforts, Sonmez and Gürel (2016) presented a hybrid optimization model (heuristic and genetic algorithm) to achieve the optimal solution of large-scale construction projects with different execution modes, multiple resources, and resource constraints. However, this group of studies has not addressed resource utilization challenges that occur during the postdisaster recovery process.

Several research studies examined prioritization techniques for postdisaster recovery and reconstruction. First, Basőz and Kiremidjian (1996) proposed a methodology to prioritize urban road bridges based on the importance and risk assessment of highways in the absence of the performance of the entire system. Cagnan and Davidson (2007) also developed a model for the recovery of infrastructure after an earthquake disaster. Their model had three components: (1) damage estimation submodel, (2) reconstruction submodel, and (3) cost (direct and indirect) estimation submodel. The output of each submodel was used as the input of the next one. Their model is capable of prioritizing the damaged elements for reconstruction based on the final output score and two other parameters—damage level and recovery accessibility.

Moreover, a group of authors conducted three studies to optimize the prioritization problem of transportation networks' reconstruction after a disaster (Orabi et al. 2009; El-Anwar et al. 2013, 2016). These studies developed an equilibrium algorithm to assess the functionality of transportation networks following a disaster event (Orabi et al. 2009), an optimization model for postdisaster reconstruction plans focusing on damaged transportation (El-Anwar et al. 2016), and an optimization model for retrofitting damaged transportation networks (El-Anwar et al. 2013). Chang et al. (2010) utilized the functionality loss of flow capacity in the transportation network to prioritize the retrofit plans considering various budget levels. They mainly focused on increasing the total functionality of the network as well as an immediate response after a disaster event. Zamanifar and Seyedhoseyni (2017) also developed a Fuzzy VIKOR (in Serbian, it is *VIseKriterijumska Optimizacija I Kompromisno Resenje*, which means multicriteria optimization and compromise solution, pronounced vikor) technique to rank roadway reconstructions after a disaster. Although invaluable efforts have been made to optimize the postdisaster 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.

Disasters and Socioeconomic Impacts

After a disaster event, infrastructure disruptions frequently lead to many types of further socioeconomic impacts, such as economic, social, health, and environmental consequences. Recently, the impact of natural disasters on society has been widely investigated by many researchers through various numerical prediction models. These models have been improved considerably by the advancement of geographic information technology (Burton 2010). For example, FEMA, an agency of the United States Department of Homeland Security, has developed the HAZUS-MH tool to estimate the economic loss from several types of natural disasters (Schneider and Schauer 2006). The disaster-related models use

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various types of data, such as different hazard scenarios, building stock information, economic data, and vulnerability functions (Watson and Johnson 2004). In these models, the concept of vulnerability denotes the physical damage or direct economic loss for physical structures at risk. They do not mainly incorporate social loss, which contributes to social vulnerability. The primary reason for disregarding the social vulnerability in postdisaster cost/loss estimation models and analyses is that these variables are limited to be quantified (Cutter et al. 2003).

Many researchers have identified the importance of social vulnerability and its inclusion in the decision-making process for postdisaster recovery. To this end, incorporating the socioeconomic characteristics of the affected community has been investigated from different perspectives in postdisaster recovery literature. Dulebenets et al. (2020) presented a multiobjective, mathematical optimization model for an emergency that takes into account the mental demand and efforts of individuals (with a focus on vulnerable population groups) during an evacuation to optimize the evacuation time and traffic routes. In separate research studies, Eid and El-Adaway (2017a, b, c) incorporate the environmental vulnerability, social vulnerability, and economic vulnerability of the host community into the objective function of an optimization model in order to achieve a sustainable and optimal recovery plan. They used agent-based modeling and mainly focused on budget distribution for postdisaster housing reconstruction projects.

On the other hand, a cluster of studies focused on developing methods and models to quantify social vulnerability to hazards from a social science perspective (Burton 2010). The social vulnerability of a region can be defined as the degree to which people and places can be harmed by a disaster event and the ability of the system to cope with and adjust to disasters' consequences (Bergstrand et al. 2015). One of the most well-established vulnerability evaluation models is the social vulnerability index (SoVI) developed by Cutter et al. (2003). This index has been developed based on analyses of specific community socioeconomic data (e.g., median age, household income, education attained, percentage of mobile homes, and so forth). The inclusion of affected communities' vulnerability and socioeconomic factors, as well as other technical and economic challenges that occur during the postdisaster recovery of the transportation network, is the main contribution of this study. All these aspects play vital roles in establishing a robust transportation network recovery plan to achieve the goal of addressing the urgent demands of affected people.

Measuring Infrastructure Disruption

Measuring infrastructure disruption aims to analyze, compare, and ultimately reduce the socioeconomic impacts. Measuring the impacts is relatively straightforward for some infrastructures, such as water distribution and electric power and water, but more complex for infrastructure that serves to enable connections across space, such as transportation systems. Faturechi and Miller-Hooks (2015) reviewed studies on measuring transportation performance after disasters and categorized the measurement approaches into three types: economic, functional, and topological. The economic approaches mainly address the aspects regarding how disasters affect the ability of travelers and freight for movement and their accessibility to destinations using the transportation infrastructure, which have direct impacts on the local economy. After disasters, employees face difficulties commuting, access to firms is disrupted for clients, interruptions in the supply chain inhibit production, and finished products cannot be easily shipped. The functional approaches mostly measure the performance of a network in terms of travel time and evaluate the disaster impact by evaluating the travel delay time within the network. The latter group of studies focuses on the location of nodes and their connectivity before and after disaster events rather than the operation of the system.

Multiagent Reinforcement Learning Model

A multiagent system is a computerized system composed of multiple interacting intelligent agents. Agent-based systems, which have been developed by researching the compounded impact of the individual actions on the system, are able to model the principles of a system and capture the dynamics of various entities that constitute the system. Therefore, agent modeling contributed to many fields of research, including engineering, economics, and social science, through simulating the cumulative impact of individual entities' behaviors on the performance of the system, such as the disaster recovery process (Eid and El-Adaway 2017c) and financing highway transportation systems (Mostafavi et al. 2016).

An agent is a computer program that reflects the actions of an entity (which can be an individual or organization) in the system (Nwana 1996). 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 in that they can replicate or learn (Macy and Willer 2002; Eid and El-Adaway 2017c). 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 (Padgham and Winikoff 2004). As a result, the intelligent agents can represent interactive entities of a system, such as stakeholders in the recovery of a community. Therefore, the postdisaster recovery process can be modeled as a multiagent system in which multiple 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 mitigation and recovery context. In one of the studies, Miles and Chang (2006) developed a framework for agent-based modeling of the postdisaster recovery of the community considering the interactions among the businesses, people, and recovery agencies. Nejat and Damnjanovic (2012) also developed a multiagent housing recovery simulation model using the game theory. The model analyzed the residents' different housing recovery options after a disaster event. Although the aforementioned research studies revealed the capability and efficiency of the agent-based system in modeling the complex environment of disaster management problems, they did not fully exploit the multiagent system abilities in providing a comprehensive, proactive decision-making system that allows decision-makers to reduce the vulnerability of the communities to future disastrous events (Eid and El-Adaway 2017c). To this end, Eid and El-Adaway (2017a, b, c) in a series of research studies deployed the agent-based modeling approach to simulate the post-disaster recovery process. They mainly focused on housing recovery with financial strategies after disastrous events for sustainable and balanced recovery, providing agent-based modeling integrating social science and post-disaster recovery.

In summary, the postdisaster recovery of infrastructures, which requires interdisciplinary approaches, has been broadly investigated with diverse perspectives and associated factors in recent years. Many researchers studied this topic from different aspects using various methodologies. One of these aspects, which is the main focus of this paper, is the prioritization of postdisaster reconstruction projects. The authors were able to confirm that considerable efforts are made to prioritize the postdisaster reconstruction of transportation infrastructure based on the physical and economic impacts of a disaster. However, a precise analysis of the underlying community vulnerability and socioeconomic factors are typically absent mainly due to the difficulty in quantifying these aspects, even though consideration of these aspects is critical for a disaster recovery plan to accomplish the goal of addressing an affected community's needs (Eid and El-Adaway 2017a). Besides, according to the presented literature review, the authors believe that there is a need for a comprehensive approach capable of optimizing the postdisaster recovery process by considering the interdisciplinary perspective.

To address these research gaps, the social impact of a natural disaster, which reflects disaster-affected communities' needs, is considered as one of the deciding factors in the proposed prioritization model. Also, this paper proposes a multiagent reinforcement learning (MARL) approach to drive optimal recovery policies and decisions for sophisticated and challenging postdisaster environments. Using this methodology allowed the authors to incorporate multidisciplinary modules, including damage assessment, transportation network analysis, and socioeconomic factors, alongside modeling the complex behavior of the system and its entities after a disaster event.

Methodology: Disaster Recovery Prioritization Model

Fig. 1 illustrates the research steps designed for developing the prioritization model. The first phase is to identify the data required for the criticality assessment of the reconstruction projects. In this step, socioeconomics, transportation networks, and postdisaster loss data are evaluated. These components are deployed in an interrelated way to assess the criticality of the damaged transportation facilities and reconstruction of them. The second phase is a model simulation utilizing a multiagent reinforcement learning for prioritization of the project portfolio in an optimized way. This step includes the following two subcomponents: (1) a MARL model, reflecting the dynamics of the system and stakeholders' behaviors; and (2) an assessment and optimization method of the network performance restoration during the reconstruction process. These two subcomponents allow the model to consider all constraints and evaluate all objectives of the postdisaster recovery process, such as socioeconomic benefits, cost, and time. The two phases of the proposed model work interactively to update the status of the system during the recovery process. These two phases will be discussed in detail in the following sections.

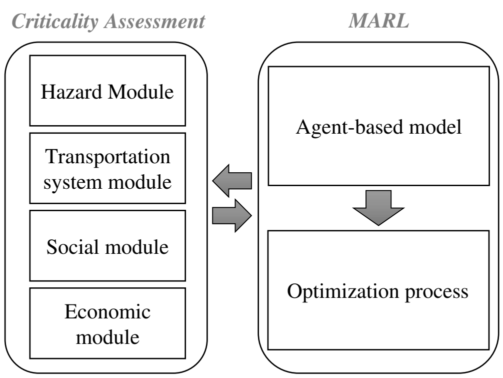

Fig. 1. Structure of the prioritization model.

Phase 1: Criticality Assessment

In this research study, the criticality of a transportation facility after a disaster is 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 damaged transportation facilities. In this study, the authors divided the required data into four categories: hazard-related data, transportation system data, social information, and economic factors. Fig. 2 indicates the four modules incorporated for collecting the aforementioned data and further analyses.

After collecting the required data, the dependency of the regions on the transportation network must be investigated to identify the criticality of the transportation facilities. Affected regions and damaged transportation facilities are highly dependent. For example, failure of a single major bridge will result in significant traffic flow disruptions over a vast region and cause difficulties for commuting, emergency response, evacuation, and economic recovery (Chang 2016). A successful postdisaster recovery plan must measure the level of criticality (interrelationship) between critical infrastructure, industries, and communities for prioritizing reconstruction projects. The level of dependency must be established by understanding the role that infrastructure played in the community. In this study, based on the zone of influence and importance of the project and analysis of the users, the criticality of each damaged segment of transportation infrastructure is determined.

Hazard Module

Physical damage to both transportation facilities and affected regions must be considered to develop an optimized recovery plan. However, damage estimation after a disaster event is a challenging and time-consuming task. To tackle this challenge, the proposed

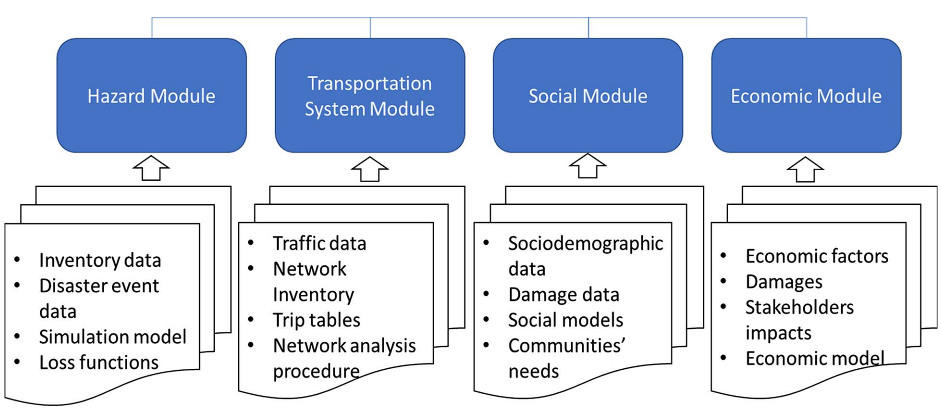

Fig. 2. Four modules of data collection and analysis for criticality assessment.

model in this study utilizes FEMA's Hazus-MH version 4.2 Hurricane Model, which is "a nationally applicable standardized methodology that contains models for estimating potential losses from earthquakes, floods, and hurricanes" (FEMA 2015). Utilizing this model in the proposed approach makes the decision-makers capable of analyzing multiple scenarios and adjusting their recovery plan.

Transportation System Module

The transportation system module intends to evaluate the disruption of services within the damaged transportation network and its gradual restoration during the recovery efforts. According to Bell and Iida (1997), there are several available metrics for evaluating the functional performance of the network, including travel time, direct cost, reliability, distance, and comfort. In this study, the authors incorporated the methodology developed by Orabi et al. (2009) into the model. This approach uses the travel time metric because of its critical effects on travelers using damaged transportation facilities. The travel time can be significantly affected by disaster events because travelers need to travel with considerably reduced speeds in longer distances than their regular and daily routes. Orabi et al. (2009) proposed the step function for performance loss restoration that shows the additional travel time decreases. The network serviceability is recovered gradually as the reconstruction works proceed. The recovered network performance loss between two consecutive milestones of the reconstruction projects can be calculated by Eq. (1). According to the proposed method by Orabi et al. (2009), immediately after the disaster event, the network experiences the maximum additional travel time, which diminishes gradually at the end of the recovery duration as all reconstruction processes are completed. Accordingly, the generated schedule of the reconstruction process is used as the input of this model to identify the dynamics of network performance loss and its restoration process during the recovery processes. This method facilitates calculating the total interruption cost of the network based on its performance

$$P = \sum_{i=1}^{n} P_{i-1} \times h_i \tag{1}$$

where P_{i-1} = performance loss at recovery milestone $i-1$; n = number of recovery milestones; and h_i = length of time between recovery milestones $i-1$ and i.

Social and Economic Modules

The socioeconomic status of a specific community can be reflected by a vulnerability index. Various social, demographic, and economic data are used in a multivariate analysis to identify the most influential factors and establish a reliable vulnerability index. In this study, a relative vulnerability score, the social vulnerability index, which is known as SoVI and developed by Cutter et al. (2003), is used to allow decision-makers to make a distinction between affected regions to allocate available funds and resources to various transportation network restoration projects more systematically and purposefully. The SoVI model is a well-established demographic and socioeconomic model that is well-known for its comprehensiveness. This model is able to evaluate the host community's vulnerability to disaster. This approach has been developed by incorporating the community's specific socioeconomic data, such as ethnicity, race, age, gender, household income, and education attained. Then these data are used for a multivariate factor analysis to define the factors that influence the social vulnerability of a specific community.

Phase 2: Disaster Recovery Multiagent Reinforcement Learning Model for Prioritization

The authors developed the proposed multiagent system, which represents the recovery process dynamics of the impacted transportation network based on the associated stakeholders' characteristics, behavior, interactions, decision-making processes, and learning behaviors. The multiple stakeholders in this context generally encompass all relevant parties, including government agencies (federal, state, and regional transportation agencies), industries involved in transportation disaster recovery and reconstruction, and communities (residents and travelers). This paper presented two main types of agents to model the stakeholders, including travelers and a transportation agency (TA).

Each agent-based model has three major components: (1) agents and their characteristics, (2) the environment, and (3) agent behavior and methods of interaction. The first step in model development is defining each of these components and finding all of the needed model inputs (Fig. 3).

Agents and Their Characteristics

Two different types of entities were considered within the multiagent model: travelers and a TA. Travelers consist of people who live in affected communities and need to commute at least once per week. Their characteristics can be considered as their sociodemographic and socioeconomic statuses, such as gender, income, age, and the number of children. *Travel demands* is also one of the other

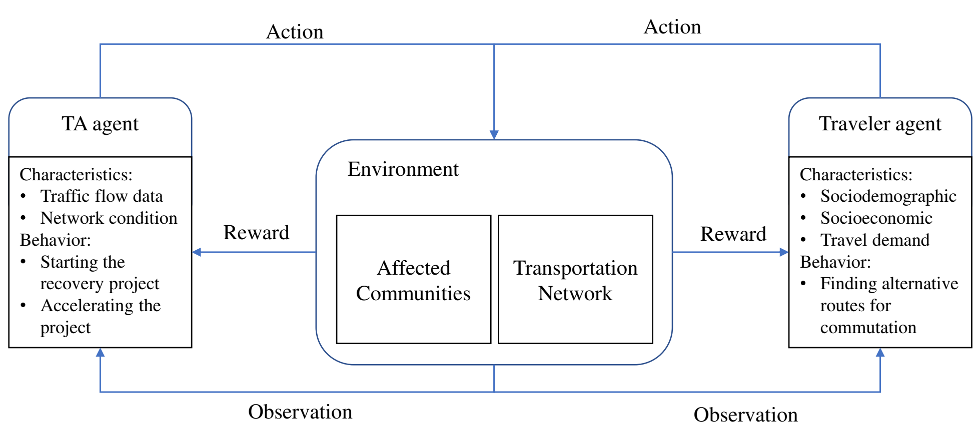

Fig. 3. Disaster recovery multiagent reinforcement learning model.

characteristics of traveler agents, which depends on the flexibility of working hours and so forth. The main objective of traveler agents is to minimize the travel time for commutation to maintain their regular livelihood. The second agent is the TA that acts as the decision-maker for the recovery process. It considers the condition of the transportation network and traffic flow for starting or accelerating the recovery projects to restore the transportation network serviceability. The main objective of the agent is to define the optimal policy for the recovery of the damaged transportation facilities.

Environment

The environment can be divided into two components. The first element is associated with the affected communities. The communities will be affected to varying extents by the disruption in services of the transportation network. Depending on the imposed damage level of the disastrous event on the host communities, some of the characteristics of traveler agents, such as socioeconomic status and travel demand, can be influenced. Spatial demographic and socioeconomic data, including the number of households and SoVI scores, should be used to define this part of the environment and its interaction with the agents. The second part of the environment is the transportation network. A disaster event causes disruption in the transportation network, which affects the traveler agents by increasing the travel time, deciding for alternative routes, and so forth. Also, the TA needs to plan the recovery process appropriately and project sequences through learning to maximize its objectives.

Agents' Behavior and Methods of Interaction

A series of if-then rules and statistical models are used for defining agents' behavior and methods of interaction. Traveler agents could choose from four different adaptations when their usual commuting pattern was disrupted. These adaptations are (1) change route, (2) depart earlier from home to work, (3) depart later from home to work, and (4) cancel work trip. The main objective of traveler agents is to minimize their daily and monthly travel costs to maintain their level of income, which directly affects their SoVI score.

The TA agent is responsible for restoring the transportation network accessibility to the predisaster level. According to the limited available resources, it should allocate the resources among the recovery projects to start them. The TA agent can start the project at any time, but there should not be any stop in the recovery process. The other option that can be taken is to accelerate a project at any time. However, the accelerated project should be finished in the accelerated form and cannot return to the normal mode. In other words, in each state, the TA agent decides to (according to the environment and availability of the resources) start projects or accelerate them until they are fully recovered.

In the proposed methodology, the agents do not have any conflicting interests. However, the presented model reflects the interactions between agents, their decisions, and the systems. The decisions of one agent can affect the system or the behavior of the other one. For example, travelers need to cancel their trip or select another route because of the disruption in the transportation network as well as the selection of a particular road for recovery purposes by the TA. In real-world problems, other conflicting interests may exist among the mentioned agents, but considering them is out of the scope of this research study.

Reinforcement Learning (RL)

According to the general setting demonstrated in Fig. 3, the agents interact with an environment. In other words, an agent perceives the state (s_t) of the system at each time step (t), and, according to the available options, needs to choose an action (a_t). The actions of all agents result in the transition of the environment to s_{t+1}, based on which the agent receives a reward (r_t). The state changes and obtained rewards are assumed to be stochastic variables that have the Markov property. Thus, the state transition probabilities and rewards depend only on the state s_t and the action a_t. It is important to note that the agents only can choose their action corresponding to s_t and have no control on or prior knowledge of the state s_{t+1} or the possible reward r_t. These quantities can be observed during the training process by interacting with the environment.

The learning process aims to maximize the expected cumulative discounted reward E, which can be defined by Eq. (2)

$$E = \left[\sum_{t=0}^{\infty} \gamma^t r_t\right] \tag{2}$$

where $\gamma \in [0, 1]$ denotes a factor discounting future rewards. The actions are selected stochastically based on a probability distribution over various actions, which is called policy (π). The $\pi(s, a)$ is the probability that action a is taken in state s under policy π [Eq. (3)]

$$\pi{:}\pi(s, a) \rightarrow [0, 1] \tag{3}$$

Because of the large number of possible (s, a) pairs in practical applications, it is not possible to keep the policy in tabular form. So, it is common to use a function approximator which has a manageable number of adjustable parameters, θ, called the policy parameter. This approach represents the policy as $\pi_\theta(s, a)$ and states the fact that the agent should take similar actions for almost similar states. Many methods of function approximators have been developed to represent the policy. For example, one of the most used methods is linear combinations of features of the state/action space [Eq. (4)]

$$\pi_\theta(s, a) = \theta T \varphi(s, a) \tag{4}$$

We focused on a class of reinforcement learning (RL) algorithms that perform gradient descent on the policy parameters for the learning process. Eq. (5), given by Sutton and Barto (1998), presents the gradient for maximizing the cumulative discounted reward

$$\nabla_\theta E_{\pi\theta}\left[\sum_{t=0}^{\infty} \gamma^t r_t\right] = E_{\pi\theta}[\nabla_\theta \log \pi_\theta(s, a) Q^{\pi_\theta}(s, a)] \tag{5}$$

where $Q^{\pi_\theta}(s, a)$ = expected cumulative discounted reward received from taking action a in state s and, subsequently, the following policy π_θ. The key concept in policy gradient techniques is to estimate the gradient by observing the trajectories of executions that are obtained by following the policy (Mao et al. 2016). The simple Monte Carlo method (Hastings 1970) is used to sample multiple trajectories and calculate the unbiased estimate of the expected cumulative discounted reward to update the policy parameter with gradient descent.

Model Assessment

In order to demonstrate the efficiency of the proposed approach, the authors developed an illustrative example, including 15 hypothetical reconstruction projects of transportation facilities spread out on

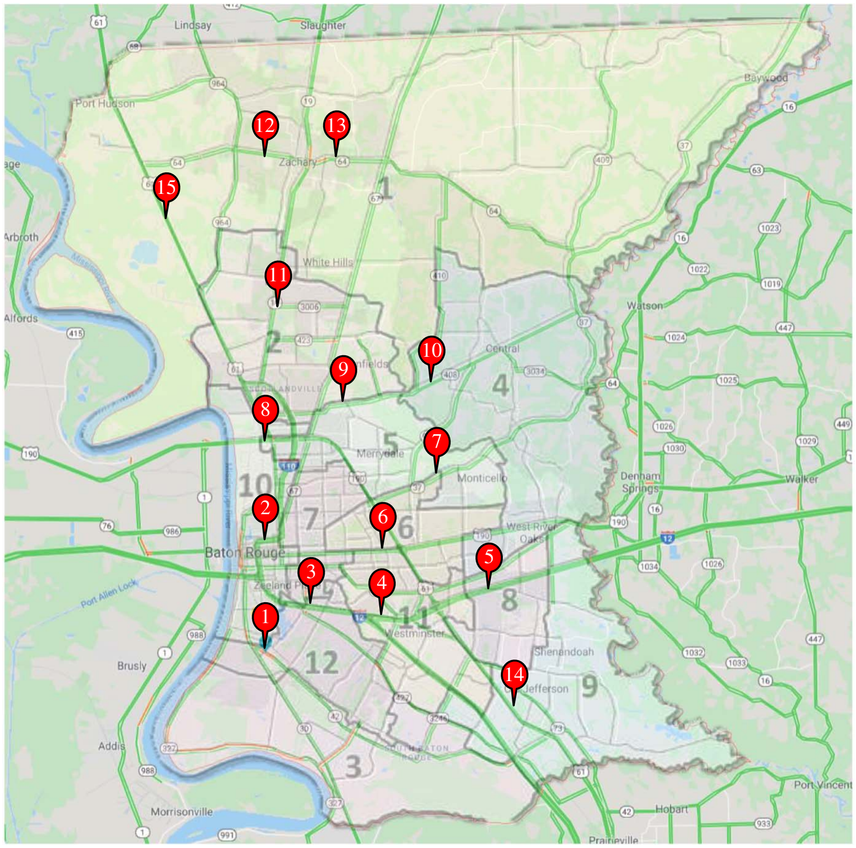

Fig. 4. Postdisaster reconstruction projects' locations. (Base map courtesy of Wikimedia Commons/CityofBR.)

the transportation network of East Baton Rouge Parish, Louisiana, after Hurricane Gustave, shown in Fig. 4. In 2008, Hurricane Gustav made landfall along the coast of Southern Louisiana. It swept through Baton Rouge, blowing down trees and power lines and carving a path of destruction. For incorporating the socioeconomic factors, the region has been divided into 12 districts with different characteristics, according to the city-parish government of Baton Rouge. Table 1 provides a summary of the zones and their attributes. The normalized SoVI scores have been calculated based on socioeconomic and sociodemographic data. Table 2 contains the information of these 15 projects that are used as model input. A simulation of Hurricane Gustav in the HAZUS-MH 4.2 software provided the following information: (1) the damage level of the transportation network; (2) the functionality level of the roads and bridges within the network; and (3) the damage levels of the districts.

Three different scenarios have been designed to evaluate the model. The first scenario was using the MARL model without learning the procedure, conducting a Monte Carlo simulation (random prioritization of projects) and collecting the data. In the Monte Carlo simulation process, the project priorities were considered as the variables and randomized based on uniform probability distribution. Then the model was simulated based on generated prioritization. The model has been randomly run for 1,000 times [calculated for a 95% of confidence level according to Eq. (6) presented

Table 1. Districts within the region of study and their characteristics

District	Normalized SoVI score	Population	Damage level ($1,000)
District 1	0.51	35,569	1,330
District 2	0.75	34,974	1,550
District 3	0.32	37,112	920
District 4	0.26	36,036	1,120
District 5	0.8	36,233	1,250
District 6	0.6	36,002	1,600
District 7	0.72	37,660	2,120
District 8	0.4	36,045	1,850
District 9	0.2	38,080	1,610
District 10	0.66	36,254	1,580
District 11	0.24	38,052	2,540
District 12	0.29	38,154	2,020

Table 2. Project portfolio input information

Project no.	Completion time (days)	Project cost ($1,000)	Damage level (%)
1	15	623	81
2	38	1,054	74
3	32	882	63
4	37	999	76
5	42	1,334	66
6	37	1,240	82
7	21	915	70
8	39	1,196	54
9	45	1,228	57
10	42	1,098	75
11	27	1,027	85
12	42	1,300	68
13	29	794	71
14	43	1,348	60
15	22	895	64

by Bukaçi et al. (2016)], and the SoVI score restoration and other data have been collected in order to create a benchmark for the learning model assessment

$$n = \left[\frac{100 \times z_c S_x}{\bar{x} E}\right]^2 \tag{6}$$

where n = number of iteration; z_c = z critical value for obtaining the specific confidence level; S_x = standard deviation of samples; $\bar{x}$ = mean value of samples; and E = error according to the selected confidence level.

As discussed previously, the recovery projects have been proposed hypothetically due to difficulty in obtaining real data. This difficulty is attributed to (1) a large number of projects in post-disaster reconstruction project portfolios after a large-scale disaster; and (2) the complexity of the real data collection because of having factors out of the scope of the paper (e.g., contractor selection and special requirements), different agencies involved in the projects, and confidentiality, so using hypothetical data allowed the authors to keep the complexity of the illustrative example low. Therefore, the Monte Carlo simulation allowed the authors to make a benchmark for further analyses and comparisons. According to the objectives of the paper, two variables of restoration time and SoVI variations have been considered as the benchmark parameters.

The second scenario is using the MARL model but excluding the SoVI score variations from the reward function in the model. In other words, the second scenario represents the optimization of the recovery time, ignoring the socioeconomic factor in the recovery process. The third scenario incorporates the SoVI score in the learning reward and, consequently, the socioeconomics in the recovery process of the transportation network.

Results and Discussion

This study analyzed results obtained from the MARL model and Monte Carlo simulation and compared the outcomes in the different scenarios to investigate the impact of the proposed MARL method on project prioritization and socioeconomic status of affected communities. In addition, the authors have calculated the SoVI score based on the collected data during the simulation runs for all scenarios and then compared them with each other. Figs. 5–7 show the normalized SoVI score variations of Districts 5, 6, 8, and 9, analyzed in the recovery process for Scenarios 1, 2, and 3, respectively. These districts have been selected to be analyzed in this study because they consist of different classes of vulnerability (high, medium, low, and very low vulnerability). Analyzing these districts can reflect how each class of vulnerability behaves during the recovery process. The average SoVI score and the most prolonged recovery period have been used for the Monte Carlo simulation scenario that allows using all the collected data. The dashed line on the figures denotes the completion time of the recovery process for the transportation network.

Comparing these figures illustrates that in all the scenarios, regardless of using any optimization method, districts with higher vulnerability take a longer time to restore than the recovery time of all of the damaged transportation facilities. In contrast, the districts with lower vulnerability (e.g., District 9) were restored even before (83, 81, and 83 days in Scenarios 1, 2, and 3, respectively) the time that the transportation network needs to fully recover (116, 85, 98 days in Scenarios 1, 2, and 3, respectively). However, it is noticeable that the learning process in Scenario 3 reduces the variation of the SoVI scores. Also, the required time for restoration decreases significantly in Scenarios 2 (average 107.83 days) and 3 (average 96.25 days) in comparison with Scenario 1 (average 125.75 days) without the optimization method.

Table 3 shows the recovery time of the transportation network alongside the SoVI restoration time for all districts. A comparison of the districts' restoration times in Scenarios 2 and 3 indicates that when the socioeconomic factors are incorporated into the optimization process, the recovery time for the transportation network will be longer than when minimizing the recovery time is the only objective of the optimization. In contrast, the midterm and long-term socioeconomic consequences of the transportation disruption on the affected communities will decrease with including those factors in the optimization objectives. In Scenario 3, there are additional districts (7 out of 15) that can be restored before the recovery of transportation facilities. In contrast, in Scenario 2, there are only three districts (out of 12) that can do so. This fact shows the efficiency of the proposed MARL and its learning model, which considers the socioeconomic factors.

For better visualization and comparison, the authors illustrate the recovery time for all districts and transportation networks in Fig. 8. The MARL method has a significantly better performance than the method with random project prioritization. As expected, the transportation recovery time in Scenario 2 is lower than one in

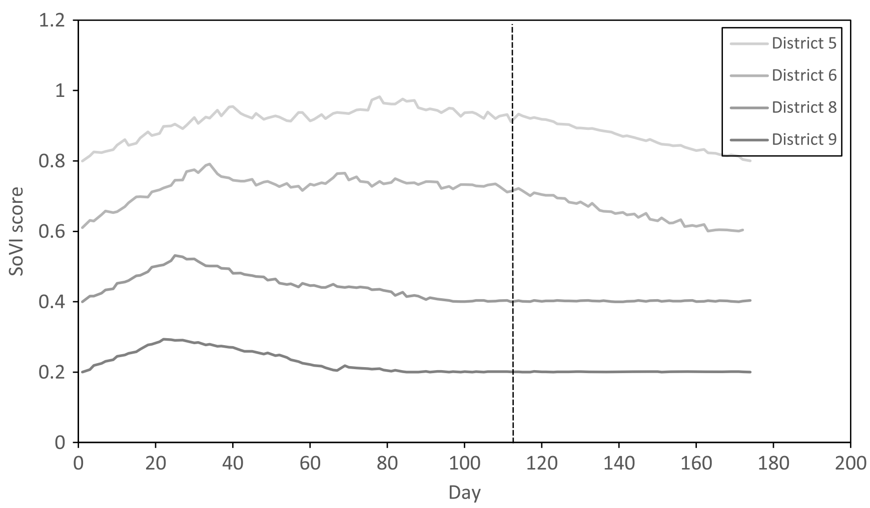

Fig. 5. SoVI score variation and restoration during the recovery process (Scenario 1: Monte Carlo simulation).

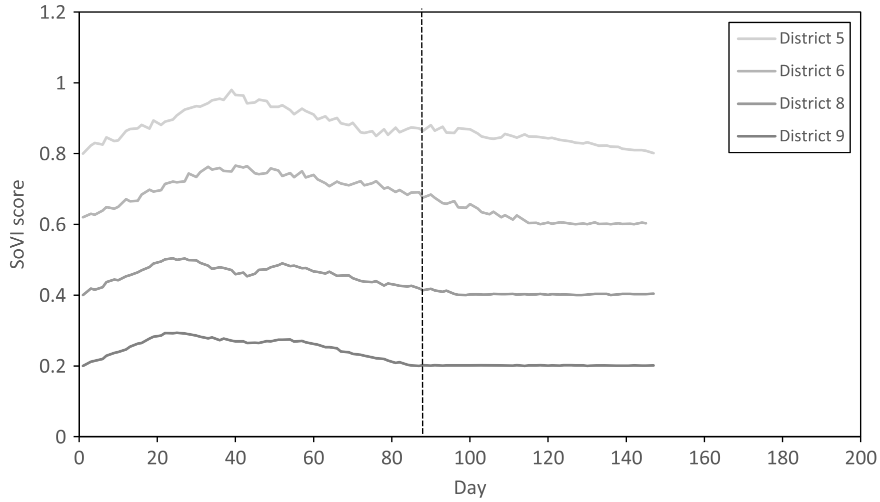

Fig. 6. SoVI score variation and restoration during the recovery process (Scenario 2: Only time minimization).

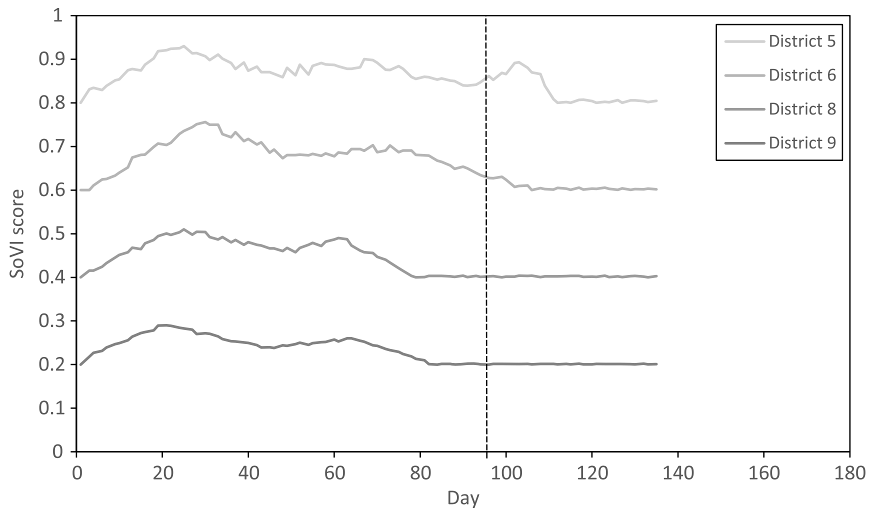

Fig. 7. SoVI score variation and restoration during the recovery process (Scenario 3: Socioeconomic optimization).

Table 3. Transportation recovery and SoVI restoration time

	Scenario 1	Scenario 2	Scenario 3
	Transportation network recovery time (days)		
	116	85	98
District	SoVI restoration time (days)		
District 1	131 (+)	110 (+)	96 (–)
District 2	165 (+)	134 (+)	110 (+)
District 3	90 (–)	102 (+)	98 (–)
District 4	88 (–)	92 (+)	85 (–)
District 5	174 (+)	147 (+)	112 (+)
District 6	162 (+)	117 (+)	105 (+)
District 7	170 (+)	128 (+)	108 (+)
District 8	98 (+)	97 (+)	80 (–)
District 9	83 (–)	81 (–)	83 (–)
District 10	163 (+)	122 (+)	106 (+)
District 11	95 (–)	81 (–)	84 (–)
District 12	90 (–)	83 (–)	88 (–)

Note: (+) = longer than the transportation network recovery time; and (–) = shorter than transportation network recovery time.

Scenario 3. However, surprisingly, the restoration of most of the districts (9 out of 12) in Scenario 3 occurred in a shorter time than the one in Scenario 2. The average time for restoration of the district in Scenario 3 is 96.25 days, which is even lower than the required time for the full recovery of the transportation network. In comparison, this average time in Scenario 2 is 107.83 days, which is 23.83 days longer than the network recovery time.

The final output of the proposed methodology is an optimized project prioritization plan that best satisfies the underlying constraints, contextual parameters, and disaster scenarios. This outcome and decision-making process offer diverse stakeholders the opportunity to prepare a disaster action strategy with consistent planning frameworks for scheduling and managing disaster recovery and resource management tasks. Table 4 illustrates the final project prioritization plan for Scenarios 2 and 3. This table contains the priority of each project and the order of starting the projects. The projects can be started and proceeded simultaneously if sufficient resources are available. Considering the constraints of financial resources, this method supports calculating the completion time of the projects for the restoration of the entire transportation

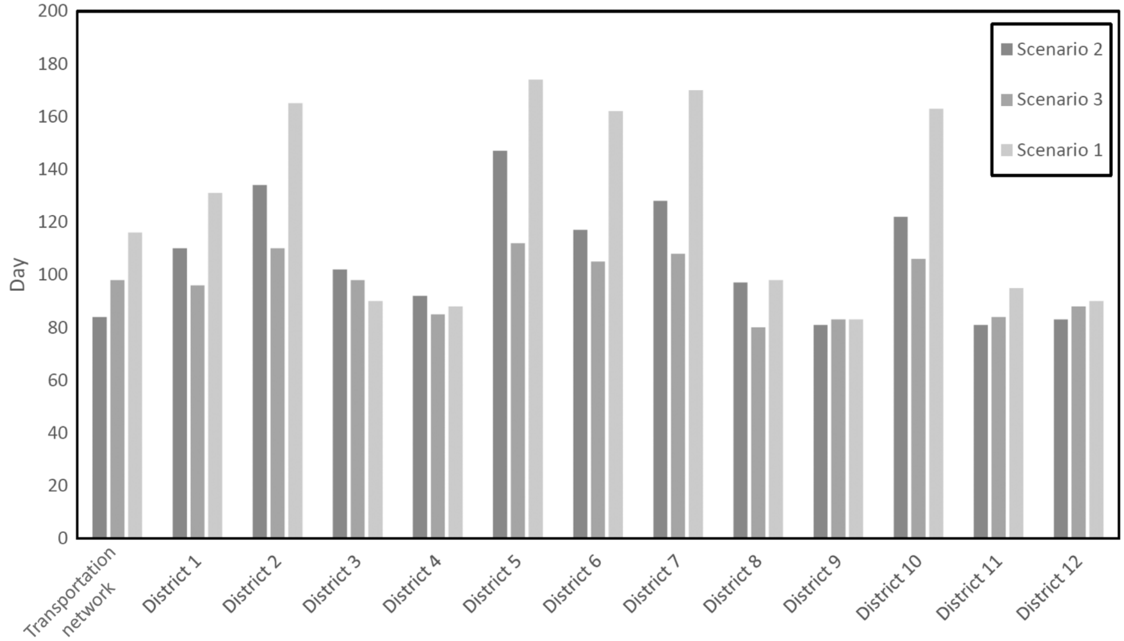

Fig. 8. Comparison of recovery time for all scenarios.

network, which are 116, 85, and 98 for Scenarios 1, 2, and 3, respectively.

Fig. 9 represents the output schedule for network recovery in Scenarios 2 and 3. According to the principles of the model, it can be assured that these schedules meet the planning constraints; however, each one pursues a specific objective. Scenario 3 is the optimal solution from the perspective of this research study because, despite its long recovery time for the transportation network than the one in Scenario 2, it provided noticeably higher community recovery rates than those in the other scenarios by targeting the more vulnerable districts.

Because time is of the essence after a disaster, the focus of this paper was to manage the transportation network disruption time to minimize the adverse effects of a prolonged recovery on regional social vulnerability. This is the primary and differentiated contribution of this paper, as other studies in this field considered multiple objectives. For example, Orabi et al. (2009) developed a multiobjective optimization model to optimize the recovery time and reconstruction cost of the transportation network. The final output of their model was similar to this paper but contains multiple sets of project priorities (optimal solution) as a Pareto front. This Pareto set requires a secondary trade-off by decision-makers to find the best-suited solution, which can be used to schedule the reconstruction process. The works conducted by El-Anwar et al. (2013, 2016) also yielded similar outputs with the goal to optimize time and cost. They took account of other details, such as contractor assignment, scheduling relationships, and cashflow. Due to the differences in the objectives, model details, and case studies, the results of this study cannot be directly compared with the related works. The proposed methodology differs from the mentioned works because it considered the midterm and long-term effects of transportation infrastructure disruption on socioeconomic factors instead of a cost function. These social effects can impose substantial indirect costs on disaster-struck communities, which are often overlooked in the cost functions. In terms of cost, this study incorporated the periodic funding limitation as a constraint in order to generate an executable scheduling plan (Fig. 9).

Table 4. Final projects prioritization plan

	Project prioritization	
Project no.	Scenario 2	Scenario 1
1	2	2
2	5	9
3	15	13
4	6	7
5	1	4
6	11	12
7	9	11
8	3	1
9	12	14
10	14	15
11	4	3
12	7	6
13	8	5
14	10	8
15	13	10

Conclusion

Due to the high dependency of communities' well-being on the transportation infrastructure, the consideration of socioeconomic factors plays a pivotal role in the success of a postdisaster recovery plan. To this end, the authors proposed a multiagent reinforcement learning model, which can capture the recovery process dynamics of the impacted transportation network based on the stakeholders' characteristics, behavior, and interactions. Deploying RL alongside the multiagent model is the foundation to model the decision-making processes and learning behaviors of major role players of recovery scenarios. The prioritizing process of the model was designed to achieve the maximum social benefits of the postdisaster reconstruction strategy while considering the severity of the physical damage of both the transportation facilities and the affected

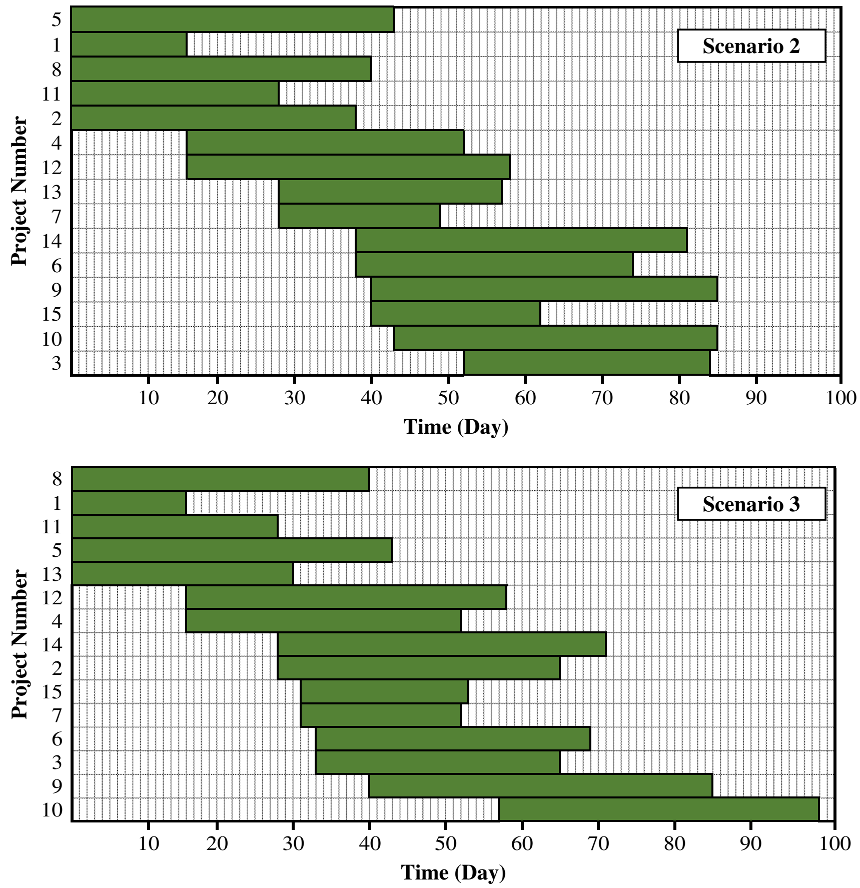

Fig. 9. Final schedule of transportation network recovery plan for Scenarios 2 and 3.

community and the dynamics of network performance restoration during the recovery process. This model facilitates the structured allocation of the limited available resources to the portfolio of postdisaster reconstruction of damaged transportation facilities based on project priority.

With the holistic perspective of the postdisaster recovery planning and deploying an interdisciplinary approach, this paper encompasses the contributions that help develop the body knowledge to the management in the engineering domains by proposing and testing a multiagent reinforcement learning model to optimize the transportation network recovery and concurrently minimize the social impact of the prolonged recovery process on disaster-struck communities. This proposed approach addresses a wide variety of parameters, including project constraints, situational context, and socioeconomic aspects, which have been rarely investigated in previous studies. Incorporating these parameters into the model provides insights for resolving multilayered and multistakeholder issues of postdisaster recovery planning and operations. Deploying MARL also helps decision-makers resolve these complex problems that are beyond the individual capacities or knowledge. In particular, this study is imperative for disaster-vulnerable communities because a coherent recovery planning framework helps all stakeholders, including government, industry, and communities, to restore promptly with well-balanced strategies in economic, societal, sustainable, and other essential aspects.

The proposed model provides a fundamental knowledge baseline that significantly enhances a comprehensive, informed decision-making process of stakeholders of governments and industries to design robust postdisaster recovery plans and execute their operation strategies logically. Also, the MARL method will enable practitioners to identify an optimal disaster recovery action plan that mutually meets affected communities' needs and resource constraints, which ultimately pursue a long-term resiliency and sustainability of communities. Thus, the proposed innovative approach can be applied in interdisciplinary engineering and management decision-making problems to optimize the decisions and actions of the system elements and ultimately improve the performance of the system.

Several simplifications have been made to test the proposed method, such as considering a few resource constraints, optimizing the priorities on the portfolio level and neglecting the single project level for resource utilization, overlooking possible conflicting interests among agents, and simplifying the cost model as well as functionality performance model of the transportation network. These simplifications can be regarded as limitations of the study that should be tackled in future studies. However, the flexibility of the proposed method allows decision-makers to adjust the model based on their needs and make room for further improvements.

The model assessment has been carried out based on a hypothetical postdisaster scenario because of a lack of available real data, which might weaken the validation process. However, in future studies, the model should be tested over different problems with various sizes and a number of variables to examine the robustness of the proposed methodology comprehensively. In future efforts, the model can be improved by considering the project-level criteria, contractor assignments, project acceleration, and other factors that affect the projects individually.

Data Availability Statement

All data, models, or codes generated or used during the study are available from the corresponding author by request.

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