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Real-Time Decision Support System for Transportation Infrastructure Management under a Hurricane Event

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16. Abstract
Under hurricane weather and traffic conditions, stakeholders need to make a series of decisions to close or restrict the traffic of vulnerable components in the transportation network for balancing traffic safety and mobility. To manage these critical components for minimizing the overall network-level losses, a deep reinforcement learning (RL)-based decision support system is employed. Specifically, the stochastic sequential decision problem of managing hurricane-impacted infrastructures is formulated as a Markov decision process, which is solved by RL methodology with deep neural network-based function approximations for the traffic control policy. It is noted that the deep RL-based minimization of overall network-level losses essentially sacrifices the traffic safety (in terms of vehicle accident risk) to obtain a significant benefit from traffic mobility (in terms of travel time), which may be unacceptable for certain risk-averse stakeholders. To address this issue, intelligent travel advisories broadcasted through various media channels are utilized, as an additional action in the RL framework, to actively redistribute the travel demand to time periods with relatively low hurricane intensity. Accordingly, the overall network-level cost can be mitigated without greatly increasing the traffic-safety losses. For concept proof, a case study on a hypothetical transportation network under hurricane events is used to demonstrate the good performance of the newly developed deep RL-based decision support system.

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INTRODUCTION

Hurricanes, as one of the most devastating natural hazards, can greatly threaten human lives and cause high economic losses. It is crucial for stakeholders from different societal sectors to make various decisions during hurricane events to mitigate hurricane-induced losses. Evacuations, albeit effective in reducing life losses, are usually reserved as the last resort for extreme cases (e.g., high-intensity landfall hurricanes) due to the associated large economic cost, which hence rarely occur (Wolshon et al., 2005a and 2005b). More frequently encountered decision-making scenarios during hurricane events are to maintain the essential functionality of communities with minimum losses under low-intensity and/or bypassing hurricanes. As the backbone in supporting essential operations of communities, transportation infrastructures could be greatly impacted by the adverse hurricane weather. For instance, long-span bridges, due to the inherent flexible structural properties, may suffer from the high hurricane winds (Wu et al., 2013a and 2013b); low-clearance coastal bridges with weak connections between substructure and superstructure are vulnerable to deck unseating induced by storm surges and waves (Ataei and Padgett, 2013); low-lying road segments are prone to inundations caused by heavy hurricane rainfall (Gori et al., 2020). These deteriorated structural performances could also compromise the traffic safety on these infrastructures. Accordingly, stakeholders need to take measures, based on hurricane weather and traffic conditions, to close or restrict the traffic flow of the vulnerable components in the transportation network for balancing traffic safety (in terms of the vehicle accident risk) and mobility (in terms of travel time). Current decision-making practices under adverse weather conditions are mainly based on empirical judgements (e.g., road/bridge closure when wind/snow/rain exceeds certain threshold) and are usually performed independently for each critical component (FHWA, 2012). These component-level studies and the obtained traffic control strategies may fail to minimize the overall network-level loss considering the high interdependencies of these transportation infrastructures (e.g., reassignment of traffic flow on the closed infrastructures may lead to severe traffic jam on open road links). In fact, effectively managing hurricane-impacted transportation infrastructures involves a complex decision-making environment encompassing coupled modules of hurricane weather, transportation infrastructure, trip generation, traffic assignment and loss calculation. As illustrated in Fig. 1, the hurricane weather module generates hurricane wind, surge/wave and rain conditions at the site of critical infrastructures, which impact the structural performance and travel demand through the modules of transportation infrastructure and trip generation, respectively; hurricane-impacted structural performance (and hence road capacity) and the travel demand serve as the input to the traffic assignment module, which determines the traffic conditions on each component of the traffic network. Based on the hurricane weather and traffic condition, the overall network-level cost (composed of traffic-safety and traffic-mobility cost) is computed through the loss calculation module; the network-level cost can be utilized by the stakeholders as the objective function to optimize the decision support system.

Optimizing the decision support system for managing hurricane-impacted transportation infrastructures is essentially solving a stochastic sequential decision problem. Specifically, the term "stochastic" refers to the uncertainties from various sources (e.g., hurricane weather and travel demand) while "sequential" highlights that the traffic control decision at current step could change the traffic condition and hence affect the decision-making of next step. This stochastic sequential decision problem could be effectively formulated as a Markov decision process (MDP), where the goal is to find the optimal decision to minimize the accumulated losses on the traffic network over the whole hurricane-impacted period. Considering that analytical solution for hurricane-traffic system dynamics is not available, the model-free reinforcement learning (RL) methodology is leveraged in this study to obtain the optimal solution to MDP in a trial-and-error fashion through interacting with the "black-box" simulators (Sutton and Barto, 2018). Furthermore, a deep neural network (DNN) is utilized to efficiently represent the decision policy (i.e., mapping from high-dimensional continuous hurricane/traffic information to the traffic control decisions) while the optimal policy (represented by DNN weights) is obtained using the deep Q learning algorithm (Mnih et al., 2015). Compared to the component-level decision-making practice, the proposed deep RL-based scheme could effectively reduce the overall network-level loss, which, however, essentially sacrifices traffic safety for higher traffic mobility. The compromised traffic safety may be unacceptable to certain risk-averse stakeholders. As a result, it may hinder the practical implementations of the deep RL-based decision support system.

To address the issue of excessively high traffic safety risk, one promising approach is to actively redistribute the travel demand to the time periods with relatively low hurricane intensity. It may be accomplished by intelligently broadcasting travel advisories to travelers through various media channels. Efforts have been made recently to incorporate various types of media tools, especially the increasingly popular social media, into effective management of transportation systems and communities under adverse weather and natural hazards. For example, Kim et al. (2018) investigated the emergency information diffusion on online social media during storm Cindy, which highlights the importance of social media as a powerful tool in disaster management (2018). Lu et al. (2018) proposed to utilize adverse weather data in social media to contribute to city-level traffic situation awareness and alerting. Fan et al. (2021) presented a vision of digital twin for city under disasters, where the social media plays an important role in extracting weather/traffic information and informs travelers of critical information. To embrace the promising future of the intelligent transportation system in a smart city, this study incorporates both traffic control commands (e.g., opening/closing infrastructures) and travel advisories (e.g., postponing trips) into the action space of the deep RL-based scheme. It is expected that the deep RL-based decision support system enhanced by intelligent travel advisories is able to maintain a low overall network-level loss without significantly increasing (or even reducing) the traffic-safety loss. The rest of study begins by formulating the stochastic sequential decision problem of managing hurricane-impacted transportation infrastructures as a MDP; then, the MDP is approached by the proposed deep RL-based decision support system with intelligent travel advisories; finally, a proof-of-concept case study on a hypothetical traffic network under hurricane events, involving aerodynamics-sensitive long-span bridges, hydrodynamics-sensitive coastal bridges and inundation-sensitive road segments, is utilized to demonstrate the good performance of the developed novel scheme.

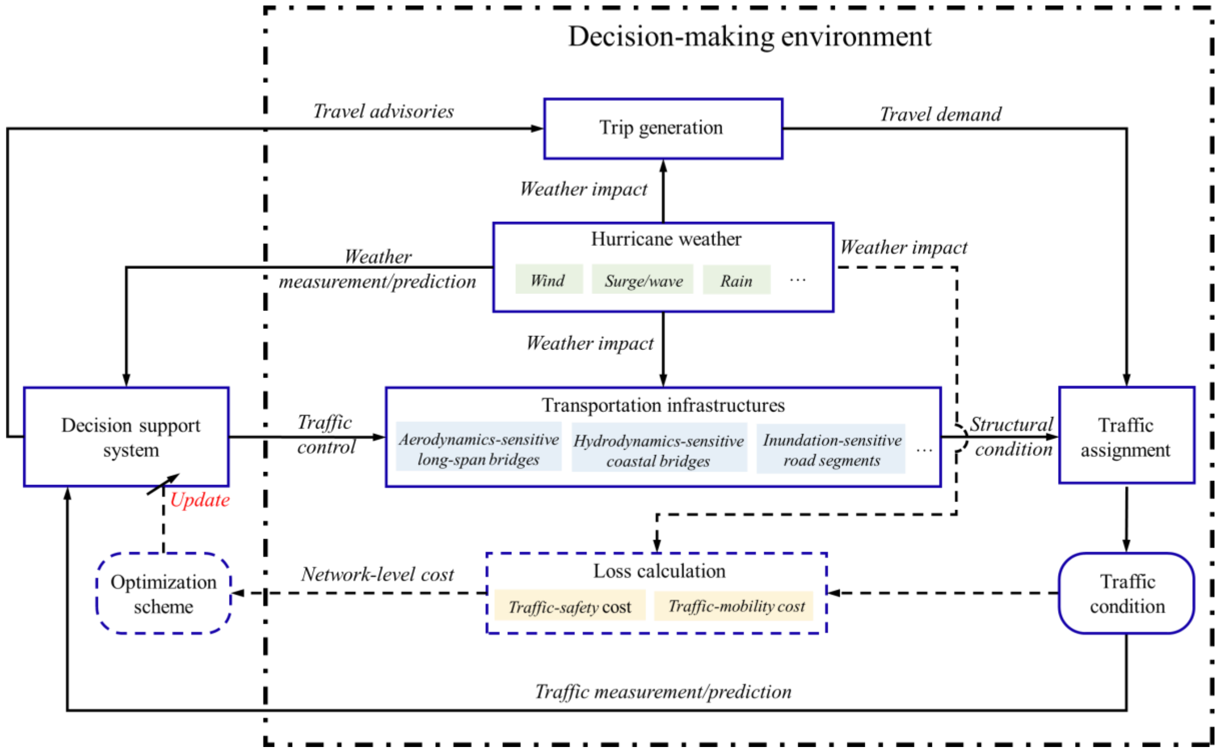


Figure 1. A general decision-making framework for managing hurricane-impacted transportation infrastructures

PROBLEM FORMULATION

The stochastic sequential decision problem of managing transportation infrastructures under hurricanes could be effectively formulated as a MDP. In MDP, an agent takes actions based on observations (i.e., states) and obtains rewards from the environment with the goal to maximize the accumulated rewards. In the case of transportation infrastructure management, the MDP state s_t at time step *t* includes both traffic condition $\boldsymbol{u}_t$ and hurricane information $\boldsymbol{w}_t$, i.e., $s_t = [\boldsymbol{u}_t, \boldsymbol{w}_t]$. Moreover, the state s_t involves both current observation (denoted by superscript *o*) and future prediction (denoted by superscript *p*), i.e., $\boldsymbol{u}_t = [\boldsymbol{u}_t^o, \boldsymbol{u}_{t+1}^p, \dots, \boldsymbol{u}_{t+h}^p]$ and $\boldsymbol{w}_t = [\boldsymbol{w}_t^o, \boldsymbol{w}_{t+1}^p, \dots, \boldsymbol{w}_{t+h}^p]$ (*h* denotes the prediction horizon). Based on current state $s_t = [\boldsymbol{u}_t^o, \boldsymbol{u}_{t+1}^p, \dots, \boldsymbol{u}_{t+h}^p, \boldsymbol{w}_t^o, \boldsymbol{w}_{t+1}^p, \dots, \boldsymbol{w}_{t+h}^p]$, stakeholders take an action a_t, to open/close critical infrastructure components and to broadcast/not broadcast travel advisories. Accordingly, the system evolves to next state $s_{t+1} = [\boldsymbol{u}_{t+1}^o, \boldsymbol{u}_{t+2}^p, \dots, \boldsymbol{u}_{t+h+1}^p, \boldsymbol{w}_{t+1}^o, \boldsymbol{w}_{t+2}^p, \dots, \boldsymbol{w}_{t+h+1}^p]$ due to the time-varying hurricane weather, change of travel demand and the traffic reassignment caused by road opening/closure. A user-designed reward (negative value of cost) $r_t = -f_m(\boldsymbol{u}_{t+1}^o) - f_s(\boldsymbol{u}_{t+1}^o, \boldsymbol{w}_{t+1}^o)$ is received at each time step, which includes cost from traffic mobility $f_m(\boldsymbol{u}_{t+1}^o)$ and safety $f_s(\boldsymbol{u}_{t+1}^o, \boldsymbol{w}_{t+1}^o)$. The cost from traffic mobility $f_m(\boldsymbol{u}_{t+1}^o)$ could be related to the vehicle travel time in the traffic network. The traffic safety-related cost $f_s(\boldsymbol{u}_{t+1}^o, \boldsymbol{w}_{t+1}^o)$, on the other hand, accounts for the vehicle accidents under hurricanes, and hence depends on both traffic condition $\boldsymbol{u}_{t+1}^o$ and weather information $\boldsymbol{w}_{t+1}^o$. The decision-making goal for stakeholders is to obtain a policy π that maps from state to action [i.e., $a = \pi(s)$] to maximize the expected cumulative reward $\mathrm{E}(\sum_{k=0}^{\infty} \gamma^k r_{t+k})$ over the whole hurricane-impacted period, where the expected value $\mathrm{E}(\cdot)$ is to consider the uncertainties from various sources (e.g., traffic condition, hurricane weather, and model predictions) and the discount factor γ (usually $0 \le \gamma \le 1$) determines the relative importance of future reward compared with immediate reward.

METHODOLOGY

There are mainly two approaches to obtain the optimal policy π_* that maximizes the expected cumulative reward, namely dynamic programming (DP) and RL (Sutton and Barto, 2018). Implementation of DP requires analytical system dynamics explicitly expressed in the form of state-transition probability (e.g., Nozhati et al., 2020), which, however, is infeasible here considering that existing models for the hurricane-traffic system are in fact "black-box" simulators with no close-form expressions. On the other hand, RL is able to obtain the optimal solution to MDP in a trial-and-error fashion through interacting with the "black-box" simulators, which eliminates the needs for explicit system dynamics and hence will be utilized in this study. As a classical RL algorithm, value-based method obtains the optimal policy indirectly through the use of value functions. Specifically, the action-value function $q_\pi(s,a)$ (also known as state-action value) is introduced, which is defined as the expected cumulative future reward starting from the state *s*, taking action *a* and following policy π afterwards. Once optimal action-value function $q_{\pi_*}(s,a)$ is known, the optimal policy could be conveniently acquired by searching a greedy action that leads to highest value, i.e., $a = \operatorname{argmax}[q_{\pi_*}(s,a)]$. As a typical value-based method, Q learning obtains $q_{\pi_*}(s,a)$ based on Bellman equation, which recursively relates the action value of current state to the sum of the immediate reward and the discounted action value of next state (Watkins and Dayan, 1992):

$$Q_{k+1}(s_t,a_t) = Q_k(s_t,a_t) + \eta_Q[r_t + \gamma \max_a Q_k(s_{t+1},a) - Q_k(s_t,a_t)] \quad (1)$$

where capital *Q* indicates an estimate of lower-case *q*; η_Q denotes the learning rate; the subscript "*k*" is the iteration number. For applications with high-dimensional continuous state space, the lookup table-based representation of Q functions in conventional Q learning needs to be extended to DNN-based Q functions. This class of RL algorithms using DNN-based function approximations is known as deep RL, which has been used to solve various complicated tasks including recent civil engineering applications to aerodynamic shape optimization of wind-sensitive structures (Li et al., 2021a) as well as active simulation of transient wind field in a multiple-fan wind tunnel (Li et al., 2021b).

This study utilizes deep RL to tackle the decision-making problem for managing hurricane-impacted transportation infrastructures. As shown in Fig. 2, RL state includes both hurricane weather and traffic information while the RL action is composed of both traffic control commands used for critical infrastructure components and travel advisories broadcasted to travelers through various media channels. RL environment is the hurricane-impacted traffic network simulated by coupled modules from different disciplines. For the hurricane weather module, a height-resolving boundary-layer model (Snaiki and Wu, 2017) is used to generate the hurricane wind while hurricane surge/wave, rainfall (and hence the inundation) are all assumed to depend on wind intensity (Snaiki and Wu, 2018; Snaiki et al., 2020). Regarding hurricane-impacted transportation infrastructures, travel risks on the long-span bridge and inundated road segment are represented by vehicle accident fragility curves (Baker, 2015). The surge/wave-induced coastal bridge damage (and hence the vehicle risk) is represented by a deck unseating fragility curve (Ataei and Padgett, 2013). To account for the effect of travel advisories on travel demand, this study assumes that only a portion of non-essential travel demand could be affected by the broadcasted travel advisories and redistributed to time periods with relatively low hurricane intensity. In addition, the traffic assignment under various decision scenarios is approached by finding the user equilibrium state (Wardrop, 1952). Considering the high-dimensional continuous state from hurricane/traffic information and the complex state-action relations, a DNN is utilized as a powerful function approximator to output the optimal actions of traffic control commands and travel advisories. The DNN weights (representing the management policy) are updated during training process by maximizing the user-defined reward (sum of weighted safety and mobility costs from three critical infrastructure components) using deep Q learning.

Deep Q learning leverages a deep Q network with the input of the high-dimensional continuous state and the output of the Q value for each discrete action. It is noted that divergence issues may occur when combining Q learning with DNN-based function approximations due mainly to two reasons, i.e., strong correlation between the consecutive samples ($s_t, a_t, r_t, s_{t+1,} a_{t+1}, r_{t+1}, \ldots$) and nonstationarity of the target $[r_t + \gamma \max_a Q_k(s_{t+1}, a)]$ in Eq. (1) (Mnih et al., 2015). To address the divergence issue caused by correlation, a replay buffer is introduced to store the past experiences, and the randomly sampled experiences from the replay buffer are utilized for updating the deep Q network. In addition to removing the strong correlation of samples, the adoption of replay buffer also enhances the training efficiency considering that past learning experiences are repetitively used. To overcome the divergence resulting from nonstationary target, a second DNN named target Q network with weights slowly tracking that of the original Q network is introduced to compute the slowly varying target Q value and hence improves stability. The details of deep Q learning, using two fully connected feedforward DNN [i.e., multilayer perceptron (MLP)] for Q network $Q_{MLP}(s, a|\boldsymbol{\theta}^{Q_{MLP}})$ and target Q network $Q'_{MLP}(s, a|\boldsymbol{\theta}^{Q'_{MLP}})$ ($\boldsymbol{\theta}^{Q_{MLP}}$ and $\boldsymbol{\theta}^{Q'_{MLP}}$ represent their weights), are shown in Algorithm 1 (Mnih et al., 2015) and schematically illustrated in Fig. 3. After offline training on the range of possible hurricane scenarios (obtained from hurricane forecast) using deep Q learning, the proposed deep RL-based decision support system could then be used online for the real hurricane events. It should be noted that the proposed scheme is generally applicable to management of transportation infrastructures under other adverse weather conditions (e.g., winter storm).

Algorithm 1. Training MLP-based policy using deep Q learning

Initialize Q network $Q_{MLP}(s, a|\boldsymbol{\theta}^{Q_{MLP}})$ and target Q network $Q'_{MLP}\left(s, a\middle|\boldsymbol{\theta}^{Q'_{MLP}}\right)$ with same weight
Initialize replay buffer as an empty set
While not convergent **do**
  Take the initial state s_0 as current state $s_t = s_0$
  For i_{step}=0, 1, 2,…., n_{step} **do**
    With probability ε_t select a random action a_t, otherwise select an action based on Q network:

$$a_t = \underset{a}{\operatorname{argmax}}\, Q_{MLP}(s_t, a|\boldsymbol{\theta}^{Q_{MLP}})$$

    Execute action a_t, observe new state s_{t+1}**,** and obtain reward r_t
    Store the experience (s_t, a_t, r_t, s_{t+1}) in replay buffer
    Sample n_{batch} experiences from replay buffer denoted as ($s_t^i, a_t^i,\ r_t^i, s_{t+1}^i$), where i=1, 2,…, n_{batch}
    For i=1, 2,…., n_{batch} **do**
      Set the target value $y_i = \ r_t^i + \gamma \max_a Q'_{MLP}(s_{t+1}^i, a|\boldsymbol{\theta}^{Q_{MLP}'})$
    End for
    Update Q network by gradient descent with learning rate η_Q:

$$\boldsymbol{\theta}^{Q_{MLP}} = \boldsymbol{\theta}^{Q_{MLP}} - \eta_Q \frac{1}{n_{batch}} \sum_{i=1}^{n_{batch}} \nabla_{\boldsymbol{\theta}^{Q_{MLP}}} [y_i - Q_{MLP}(s_t^i, a_t^i|\boldsymbol{\theta}^{Q_{MLP}})]^2$$

    Assign new state as the current state $s_t = s_{t+1}$
    For each N_{update} steps copy the weight of Q network to target Q network: $\boldsymbol{\theta}^{\boldsymbol{Q'_{MLP}}} = \boldsymbol{\theta}^{Q_{MLP}}$
End for
End while

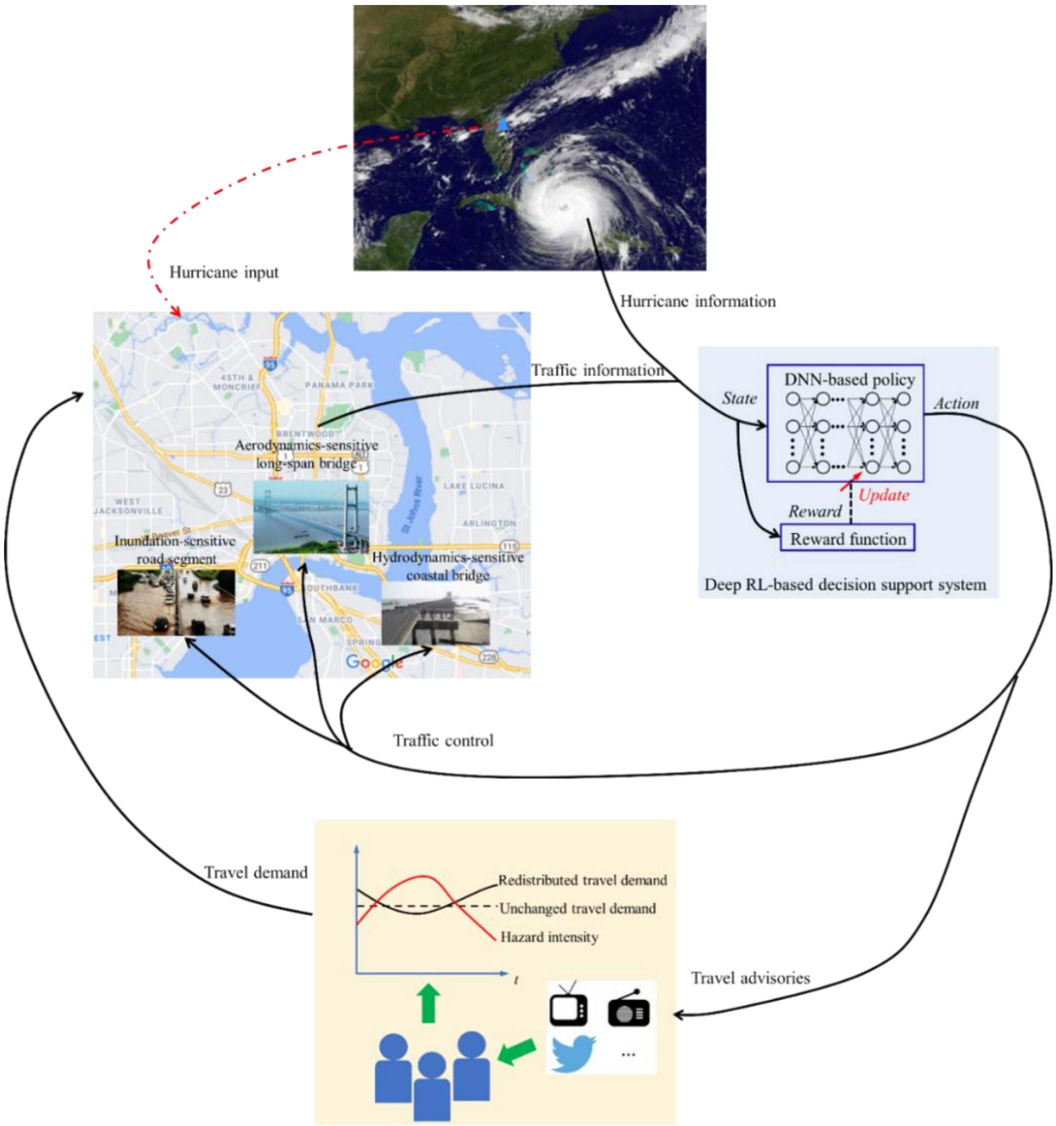


Figure 2. Schematic of proposed deep RL-based decision support system with intelligent travel advisories

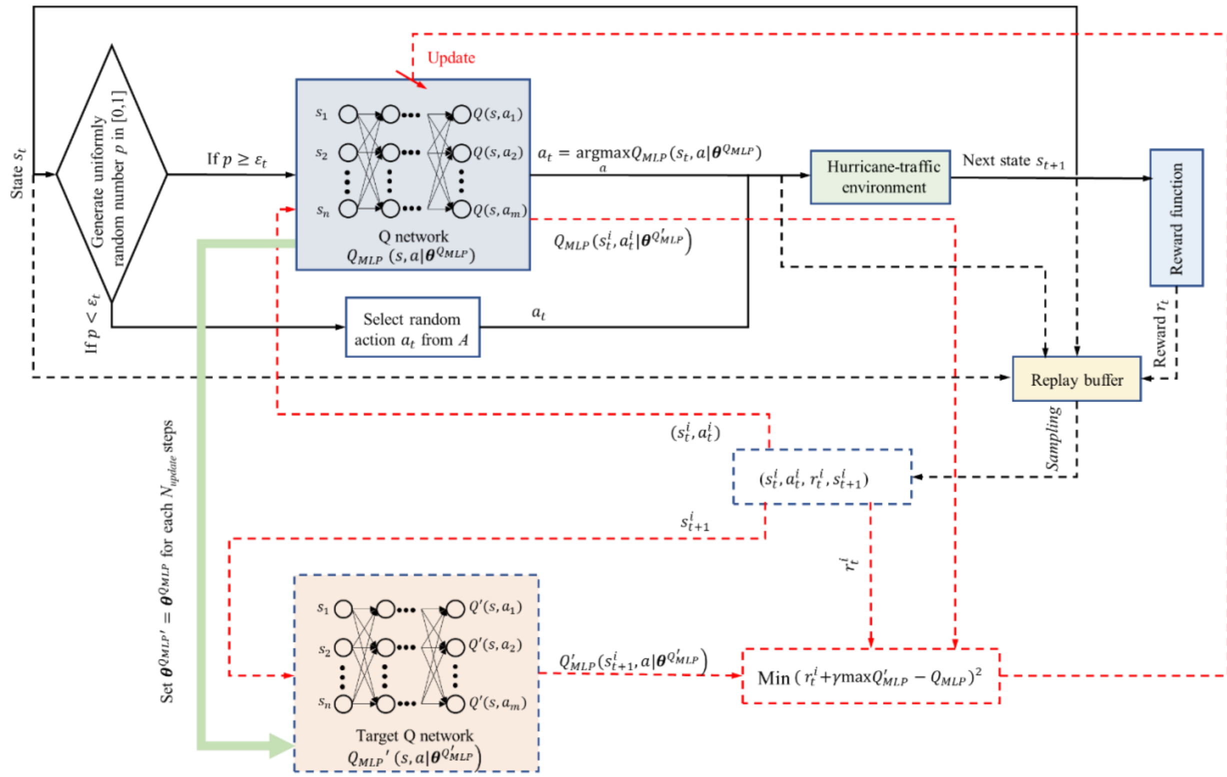


Figure 3. Schematic diagram of deep Q learning in the hurricane-traffic environment

CASE STUDY

The case study considers a hypothetical traffic network under hurricane impact. As shown in Fig. 4, the traffic network encompasses three critical hurricane-impacted components, namely an aerodynamics-sensitive long-span bridge, a hydrodynamics-sensitive coastal bridge and an inundation-sensitive road segment. The traffic network, although simple for demonstration purposes, is intentionally designed to accommodate common features in real applications. There are two origins (i.e., Nodes 1 and 2) and two destinations (i.e., Nodes 10 and 11) in the traffic network, where associated travel paths need to cross the river. Only one (Link 6-8) of the two river-crossing links (Links 5-7 and 6-8) is considered to be significantly impacted by hurricanes, which makes it possible to maintain the essential functionality of the traffic network; the long-span bridge and the coastal bridge are highly dependent on each other (considering traffic flow on Link 2-4 will eventually go to Link 6-8) while the inundated road segment (Link 1-5) is less dependent on the other two critical components. The road link properties in terms of free-flow travel time and link capacity are presented in Table 1.

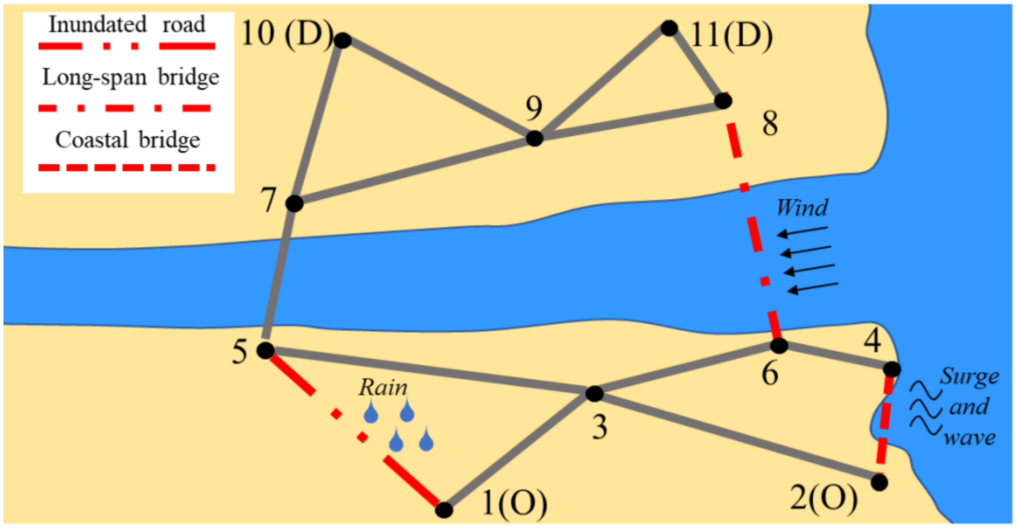


Figure 4. A hypothetical hurricane-impacted traffic network

Table 1. Road link properties of the traffic network

Link number	Connected nodes	Free-flow travel time (min)	Link capacity (veh/h)
1	1-3	6	3000
2	1-5	6	3600
3	2-3	6	3600
4	2-4	3	3600
5	3-5	6	4200
6	3-6	6	3600
7	4-6	3	3600
8	5-7	6	4800
9	6-8	6	4800
10	7-9	6	3600
11	7-10	6	3600
12	8-9	6	3600
13	8-11	6	3600
14	9-10	6	3600
15	9-11	6	3600

A low-intensity bypassing hurricane (shown in Fig. 5) is used to evaluate the performance of the proposed decision support system. This study assumes a relatively short duration of the considered hurricane and adopts a 12-hour (daytime) decision-making window with one-hour interval (a reasonable interval length for sequential decision-making of stakeholders). Hurricane weather observation $\boldsymbol{w}_t^o$ is composed of four relevant hazard intensity measures $[V_t^o, H_t^o, \eta_t^o, d_t^o]$, where V_t^o is the hurricane wind speed at the site of long-span bridge; H_t^o and η_t^o are the significant wave height and surge elevation at the coastal bridge, respectively; d_t^o denotes the inundation depth of the road segment. Hurricane weather prediction $\boldsymbol{w}_{t+1}^p$ is the noisy estimate of the true value $\boldsymbol{w}_{t+1}^o$ with $V_{t+1}^p = V_{t+1}^o(1+N_V)$, $H_{t+1}^p = H_{t+1}^o(1+N_H)$, $\eta_{t+1}^p = \eta_{t+1}^o(1+N_\eta)$ and $d_{t+1}^p = d_{t+1}^o(1+N_d)$, where N_V, N_H, N_η and N_d are the selected random noises. It is noted that "future" observation is based on the information of best track, and the prediction-related random noises are assumed to follow independent zero-mean Gaussian distributions with standard deviation determined based on prediction errors (as illustrated by the possible hurricane track range in Fig. 5).

To generate the time-varying mean wind speed V_t^o at the bridge site (assuming 25m elevation of bridge), a height-resolving hurricane boundary-layer model developed by Snaiki and Wu (2017) is used in this study, where the model input is the storm parameter of central pressure deficit $\Delta p(t)$, radius to maximum winds $R_{max}(t)$, heading direction $\varphi_a(t)$, translational speed $c(t)$ and the relative location of bridge with respect to the hurricane center in terms of radial distance $r(t)$ and azimuth angle $\theta(t)$. The details regarding the hurricane wind model are referred to Snaiki and Wu (2017). The bypassing hurricane tracks are determined such that the bridge site wind speed starts at 10m/s (assuming the decision-making system is triggered at 10m/s wind speed) and the peak wind speed is constrained between 25m/s to 30m/s. In addition, the peak wind is designed to occur around 5 to 7h after initialization of the decision-making process for the purpose of showing a complete decision sequence involving open-close-reopen of the infrastructures. Despite the rapid development of high-fidelity simulations for coupled wind-wave-surge and wind-rain-flood fields, they may be infeasible for the real-time decision support system considering the required large amount of simulations of hurricanes under uncertainties. As a result, this study simply considers that the storm surge/wave at the coastal bridge and the hurricane rainfall (and hence the road inundation depth) are dependent on wind intensity measure (Snaiki and Wu, 2018; Snaiki et al., 2020). It is also noted that unsynchronized behaviors may exist in these hazards. For instance, the storm surge/wave may propagate to the coastal areas before the hurricane wind arrives. There may be a time delay for the maximum inundated depth with respect to the maximum wind speed due to, for example, the saturation of the drainage system. In this study, these unsynchronized behaviors are considered by relating the hazard intensities to wind speed with introduced time lags using the following relation $H_t^o = f_{HV}\left(V_{t+t_H}^o\right) + N_{HV}$, $\eta_t^o = f_{\eta V}\left(V_{t+t_\eta}^o\right) + N_{\eta V}$ and $d_t^o = f_{dV}\left(V_{t+t_d}^o\right) + N_{dV}$, where t_H, t_η and t_d are the time lags while N_{HV}, $N_{\eta V}$ and N_{dV} are random noises to consider the uncertainties on the predefined relations of f_{HV}, $f_{\eta V}$ and f_{dV}. Fifty random realizations of the hurricane weather conditions based on linear functions of f_{HV}, $f_{\eta V}$ and f_{dV} with time lags $t_H = 1\text{h}$, $t_\eta = 2\text{h}$ and $t_d = -1\text{h}$ are shown in Fig. 6.

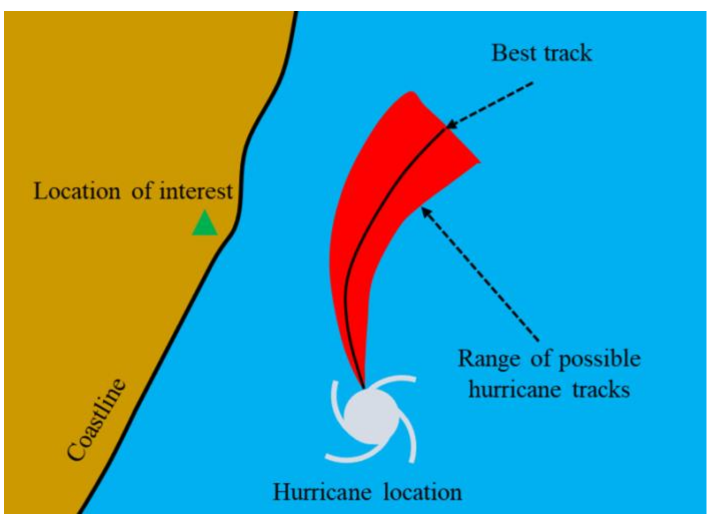
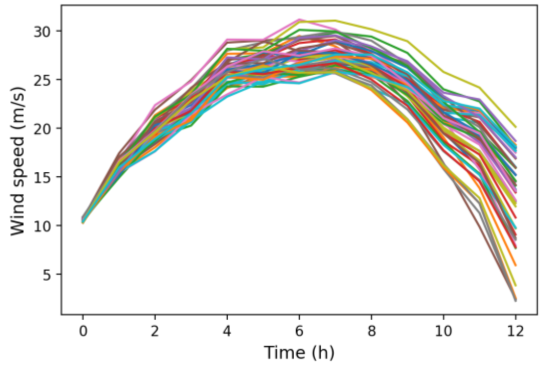
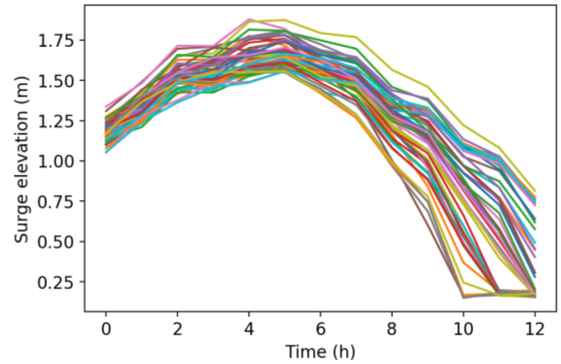


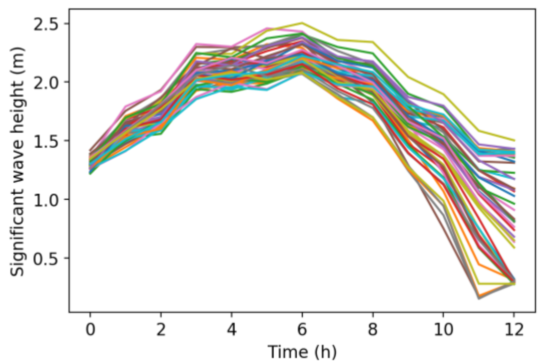
Figure 5. Range of possible tracks of a bypassing hurricane



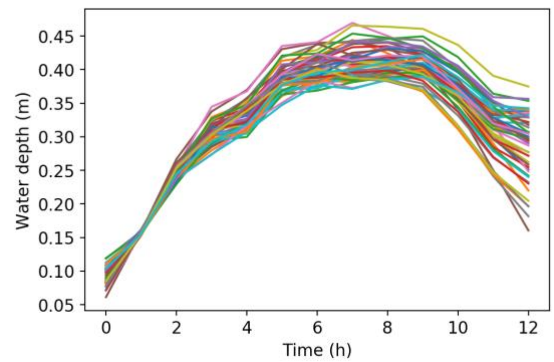
(a) Wind speed



(b) Surge elevation



(c) Significant wave height



(d) Inundation depth

Figure 6. Fifty random realizations of the hurricane weather conditions for the critical infrastructures

The adverse hurricane weather could greatly impact the performance of critical infrastructure components and hence the traffic safety on them. This could be evaluated using fragility curves, which map hazard intensities to vehicle damage probabilities. For the aerodynamics-sensitive long-span bridges, both the high aerodynamic load on the vehicles and the significant wind-induced bridge vibrations contribute to the traffic-safety issue (Baker, 2015; Zhou, Y. and Chen, S., 2015). Moving beyond conventional approach of using critical wind speed as a function of vehicle speed for vehicle instability (Baker, 1987), Baker (2015) introduced the uncertainties in vehicle parameters and speeds and utilized a fragility curve relating the wind speed V^ovehicle to accident probability P_{lb}:

$$P_{lb} = \begin{cases} 0 & 0\text{m/s} < V^o \leq 20m/s \\ (V^o - 20)/30 & 20\text{m/s} < V^o \leq 50\text{m/s} \\ 1 & V^o > 50\text{m/s} \end{cases} \tag{2}$$

Regarding the inundated road segments, critical water depth related to vehicle speed is also available (Pregnolato et al., 2017), which, using a similar approach as in Baker (2015), leads to a fragility curve relating accident probability P_{ir} to water depth d^o:

$$P_{ir} = \begin{cases} 0 & d^o \leq 0.25\text{m} \\ 25(d^o - 0.25)^2 & 0.25\text{m} < d^o \leq 0.45\text{m} \\ 1 & d^o > 0.45\text{m} \end{cases} \tag{3}$$

The use of Eqs. (2) and (3) could help to demonstrate the generality of the proposed scheme as applied to both linear and nonlinear scenarios. Instead of directly examining vehicle safety on hydrodynamics-sensitive coastal bridges, existing studies usually target at investigating the unseating probability of the bridge deck. Ataei and Padgett (2013) developed an empirical relation between the unseating damage probability P_{cb} and the intensity measures of wave H^o and surge η^o:

$$P_{cb} = \begin{cases} 0 & 0.1H^o + 0.25\eta^o - 0.35 \le 0\text{m} \\ 0.1H^o + 0.25\eta^o - 0.35 & 0\text{m} < 0.1H^o + 0.25\eta^o - 0.35 \le 1\text{m} \\ 1 & 0.1H^o + 0.25\eta^o - 0.35 > 1\text{m} \end{cases} \tag{4}$$

It is noted that the vehicle accident probability here is set to be the same with the deck unseating probability.

Variation in travel demand during hurricanes can change traffic condition and hence impact decision-making. It is known that travelers may voluntarily choose to cancel or delay their travel plans due to the adverse weather condition even without explicit instructions from authorities (Cools et al., 2010). This time-varying travel demands during hurricanes is very complex and location-dependent, which are usually estimated by survey studies and/or traffic measurement. Considering the focus is to investigate the benefit of active redistribution of travel demand through broadcasting travel advisories, this study simply assumes constant travel demand when no travel advisories are broadcasted. Specifically, the travel demands for O-D 1-10, 1-11, 2-10 and 2-11 in the designed traffic network are respectively assumed to be 4500, 4750, 5000 and 4250 vehicles/hour. The conservation of travel demand during the decision-making window (i.e., no trip cancellation) also ensures a fair comparison of different decision-making schemes. Furthermore, this study only considers the travel advisory of postponing trips since it is easier and more reasonable to convince travelers to delay trips compared to suggesting early departures. The mechanism of the postpone-trip advisory affecting travel demand distribution is schematically shown in Fig. 7. After broadcasting the travel advisory of postponing trips at time *t*, a portion of travel demand at future steps is moved to the ending time steps of the decision-making period (for the conservation of travel demand). Furthermore, this study assumes that only the travel demand immediately after the broadcasted travel advisories is impacted considering that travelers may tend to finalize their trip decisions according to the latest travel advisories. Specifically, this study assumes a small portion (randomly distributed between 5% and 7%) of the next-step travel demand is impacted by the broadcasted travel advisories considering that only part of the non-essential travelers that have access to the media may change their travel plans. The impacted travel demand is redistributed to the last two steps of the decision-making window (70% to the last step and 30% to the second to last step) It is noted that 100% of the impacted travel demand of the second to last step is redistributed to the last step. In addition, this study assumes that the travel advisories have the same effect on the travel demand of all four O-D pairs.

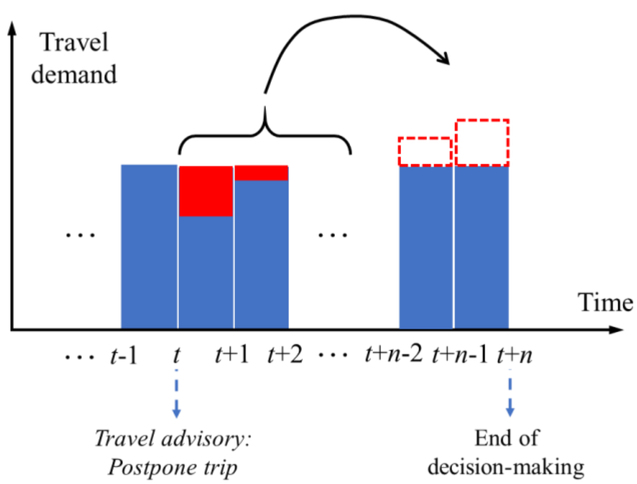


Figure 7. Effect of travel advisories on travel demand

To obtain the optimal traffic control decisions for critical infrastructures, it is necessary to evaluate the network performance (e.g., travel time and traffic volume on each road link) under different traffic control actions and travel advisories, which is a typical traffic assignment problem. This study assumes that stakeholders can only determine the opening/closure of critical infrastructure components and broadcast travel advisories without direct control over individual route choices. Accordingly, the traffic assignment problem is approached by finding the state of user equilibrium (Wardrop, 1952), where all alternative routes have equal travel time and no single user could reduce the travel time by unilaterally changing the travel route. It is known that finding the user equilibrium state is equivalent to solving the following optimization problem while meeting the travel demand for each origin-destination (OD) pair (Bell and Iida, 1997):

$$\min_{\boldsymbol{x}} f(\boldsymbol{x}) = \sum_{k=1}^{N_{link}} \int_0^{x^k} T^k(x)\mathrm{d}x \tag{5}$$

where $\boldsymbol{x}$ represents the traffic flow vector composed of all link flows x^k ($k = 1,2,\dots,N_{link}$); N_{link} denotes the number of road links in the traffic network; $T^k(x)$ is the link performance function determining the link travel time T^k given the link flow *x*. One commonly used link performance function is in the following form (Bureau of Public Roads, 1964):

$$T^k\left(x^k\right) = \overline{T^k}\left[1 + 0.15\left(\frac{x^k}{c^k}\right)^4\right] \tag{6}$$

where $\overline{T^k}$ is the free-flow travel time of link *k* and c^k is the road capacity. It is noted that both free-flow travel time and road capacities of these critical infrastructures may be impacted by the hurricane weather considering, for example, travelers tend to drive with more caution under adverse weather conditions. The hurricane-impacted free-flow travel time and road capacity of the long-span bridge and inundated road are respectively assumed to be:

$$T^{lb} = \begin{cases} 6 & 0\mathrm{m/s} < V^o \leq 20m/s \\ 6 + (V^o - 20)/10 & V^o > 20\mathrm{m/s} \end{cases} \tag{7}$$

$$c^{lb} = \begin{cases} 4800 & 0\mathrm{m/s} < V^o \leq 20m/s \\ 4800 - 30(V^o - 20) & V^o > 20\mathrm{m/s} \end{cases} \tag{8}$$

$$T^{ir} = \begin{cases} 6 & 0m < d^o \leq 0.25\mathrm{m} \\ 6 + 10(d^o - 0.25) & d^o > 0.25\mathrm{m} \end{cases} \tag{9}$$

$$c^{ir} = \begin{cases} 3600 & 0m < d^o \leq 0.25\mathrm{m} \\ 3600 - 1000(d^o - 0.25) & d^o > 0.25\mathrm{m} \end{cases} \tag{10}$$

where superscript *lb* and *ir* denote the long-span bridge and the inundated road, respectively. The weather effect on the coastal bridge is not considered here because the storm surge/wave loads mainly affect the structural safety instead of serviceability.

The link flows under user equilibrium state are obtained iteratively using Frank-Wolf algorithm (Bell and Iida, 1997), which is schematically shown in the flowchart of Fig. 8. It should be pointed out that the user equilibrium-based model used in this study is a quasi-static approach with many simplifications. Further investigations on advanced models of hurricane-impacted traffic network (e.g., agent-based modeling that captures the behavior of individual vehicles) are required to more accurately simulate the system performance.

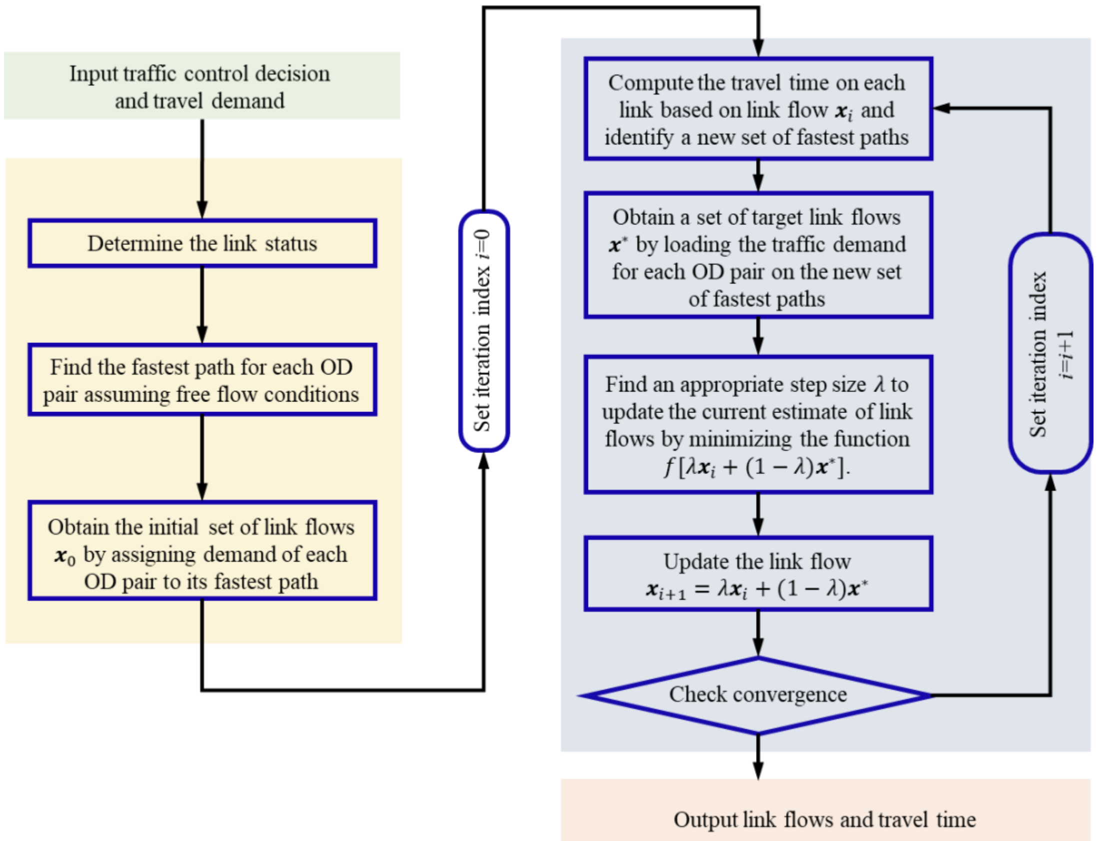


Figure 8. Flowchart of obtaining user equilibrium using Frank-Wolf algorithm

With traffic condition obtained from traffic assignment module, the overall network-level loss could be computed through loss calculation module for evaluating and optimizing decision-making strategies. The reward function r_t (the negative value of cost) could be designed as sum of weighted costs from traffic mobility and traffic safety:

$$r_t = -A\sum_{k=1}^{N_{link}} x_{t+1}^k T_{t+1}^k - B_{lb} \times P_{lb}(V_{t+1}^o) \times x_{t+1}^{lb} - B_{cb} \times P_{cb}(H_{t+1}^o, \eta_{t+1}^o) \times x_{t+1}^{cb} - B_{ir} \times P_{ir}(d_{t+1}^o) \times x_{t+1}^{ir} \tag{10}$$

where the first term is the traffic mobility-related cost (i.e., the sum of travel time for all vehicles in the network); while the other three terms represent the traffic-safety cost from vehicle accidents on the three critical infrastructure components; $P_{lb}(V_{t+1}^o)$, $P_{cb}(H_{t+1}^o, \eta_{t+1}^o)$ and $P_{ir}(d_{t+1}^o)$ are the vehicle accident probabilities defined previously; x_{t+1}^{lb}, x_{t+1}^{cb} and x_{t+1}^{ir} are the traffic flow on the three critical infrastructures; A, B_{lb}, B_{cb} and B_{ir} are the relative weights of these cost terms. In this study, the relative weights are chosen to be $A = 1$, $B_{lb} = 1000$, $B_{cb} = 4$ and $B_{ir} = 125$. The large value of B_{lb} is due to the high severity of car accidents on a long-span bridge (e.g., rollover and sideslip) while the low value of B_{cb} is to account for the low possibility of a vehicle happening to run on an unseating span of the coastal bridge. It should be noted that determining these relative weights is essentially based on stakeholders' value judgement and requires further investigations.

After constructing the hurricane-traffic environment, the DNN-based decision support system is trained using RL methodology. In this study, the DNN input (i.e., state) is selected to be:

$$s_t = [x_t^1, x_t^2, \dots, x_t^{N_{link}}, V_t^o, H_t^o, \eta_t^o, d_t^p, V_{t+1}^p, H_{t+1}^p, \eta_{t+1}^p, d_{t+1}^p, n_t^{ta}] \tag{11}$$

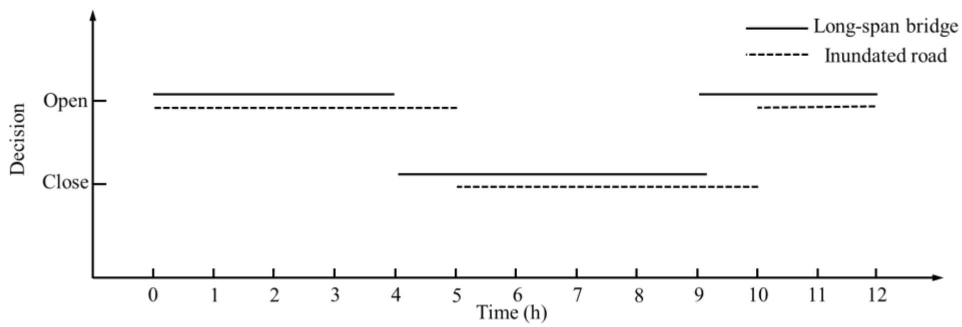
where n_t^{ta} is the number of travel advisories that have been broadcasted up to the current time step. Intuitively, n_t^{ta} provides the information on how many trips have been postponed to the final steps, which is important for decision-making because it may be undesirable to postpone trips if the travel demand postponed to the final steps is already high and the associated traffic-mobility cost of the final steps is large. It is noted that the traffic prediction for next step is not explicitly included in the state since it could be fully determined by current traffic condition, the enforced traffic control and the broadcasted travel advisories. It is also worthwhile to mention that prediction with longer horizon may be important for decision-making in more complicated cases, considering, for example, some traffic control actions may involve preparation stages that need to be deployed in advance. Although not discussed in this study, it is straightforward to include long-term predictions as additional states in the proposed framework.

The action a_t for the deep RL-based scheme with travel advisories is a_t= $[a_t^{lb}, a_t^{ir}, a_t^{ta}]$, where a_t^{lb} and a_t^{ir} are the binary actions to open/close the aerodynamics-sensitive long-span bridge and the inundation-sensitive road segment, respectively; a_t^{ta} is binary action to "do nothing" or "broadcast the travel advisory of postponing trips". The reason that the traffic control of the hydrodynamics-sensitive coastal bridge is not included is to consider general situations, where stakeholders may not have enough resources to control all hurricane-impacted infrastructures. It is obvious that adding the action of travel advisories a_t^{ta} expands the action space of the plain-vanilla deep RL-based scheme with a_t= $[a_t^{lb}, a_t^{ir}]$, which hence leads to a better (at least not worse) performance in terms of minimizing hurricane-induced losses.

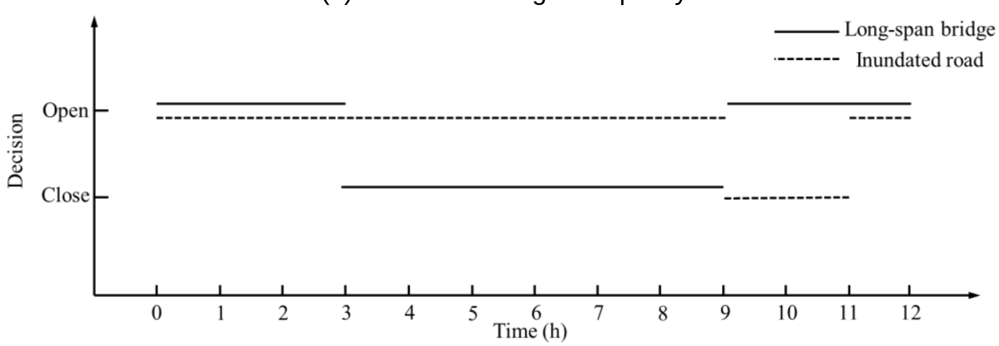
The deep RL-based decision support system with intelligent travel advisories is first trained offline on the set of possible hurricanes before online application to the real hurricane impacting the location of interest. The hyperparameters in Table 2 are used to train the proposed decision support system using deep Q learning. It is found that the most critical hyperparameter to the learning performance is the exploration probability ε_t, which is set to decay exponentially as learning proceeds, i.e., $\varepsilon_t = 0.999995^{n_i}$ (n_i is iteration number). Training of 45000 episodes (each episode is a realization of a random hurricane scenario) is required to reach convergence, which takes around four hours on a personal computer (Intel i7-6700 CPU @ 3.40 Hz). Two hurricane scenarios are used to test the performance. Hurricane Case A has a peak wind speed of 26m/s. The results of conventional component-level decision-making (denoted here as the base policy), plain-vanilla deep RL-based policy and deep RL with travel advisories are shown and compared in Fig. 9. Specifically, the base policy indicates that the long-span bridge is closed when the next-step wind speed prediction (with prediction noise considered) exceeds 22.5m/s while the inundated road is closed when the next-step water depth prediction (with prediction noise considered) is over 0.3m. The values of 22.5m/s and 0.3m are chosen to be slightly higher than the threshold values used previously for the accident probability, considering that stakeholders may have, to some extent, taken into account the component-level traffic mobility-safety tradeoff. Compared to the base policy, the plain-vanilla deep RL-based policy avoids closing the long-span bridge and the inundated road simultaneously under hurricane Case A, which reduces overall network-level cost by 16% at the expense of increasing the traffic-safety cost by 75%. On the other hand, travel advisory-enhanced deep RL-based policy broadcasts the "postpone-trip" advisories from *t*=3h to 9h, which, compared to base policy, reduces overall network-level cost by 27% while obtaining 17% reduction in the traffic-safety cost. Particularly, due to the decreased travel demand caused by travel advisories, the optimal decision for *t*=7h to 9h becomes to close both the infrastructure components, which contributes to the reduction of traffic-safety cost. The use of travel advisories only expands the solution space for optimizing the overall network-level cost (sum of traffic-safety and traffic-mobility costs) without explicit restrictions on traffic-safety cost, hence, it does not necessarily guarantee the reduction in traffic-safety cost compared to base policy. This observation is demonstrated by the simulation result under hurricane Case B with peak wind speed of 29m/s (see Fig. 10). Under hurricane Case B, the plain-vanilla deep RL-based policy, compared to based policy, obtains 9% reduction in overall network-level cost while increasing the traffic-safety cost by 51%. On the other hand, deep RL-based policy with broadcasted travel advisories from t=2 to 10h leads to a larger reduction in network-level cost (22%) with a smaller increase (14%) in traffic-safety cost.

Table 2. Hyperparameters of deep Q learning

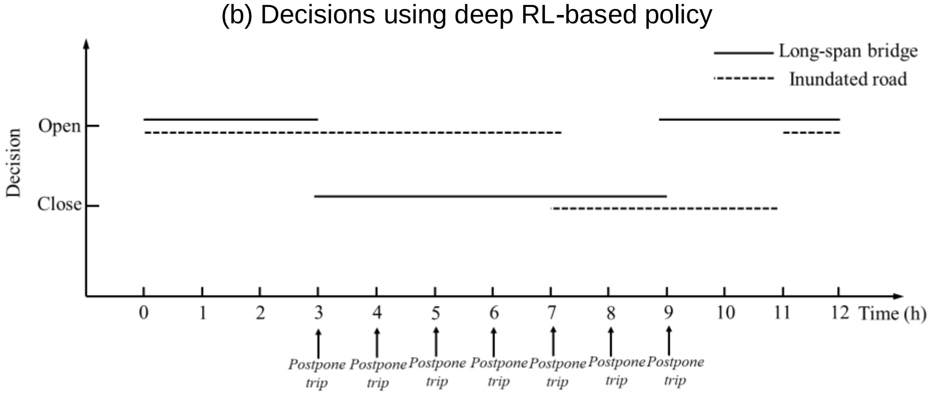
Hyperparameters	Values
Number of layers	5
Number of neurons of each layer	60
Learning rate η_Q	0.00015
Activation functions in hidden layers	Rectified linear unit
Update frequency of target Q network N_{update}	2000
Batch size n_{batch}	128
Exploration probability ε	0.999995^{n_i} (n_i is iteration number)



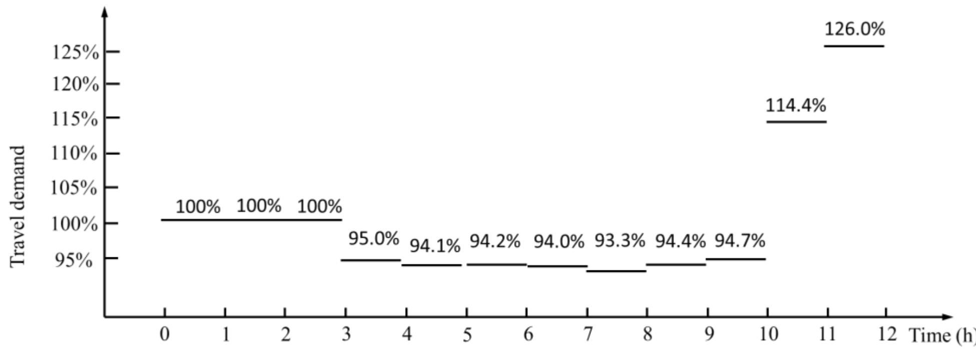
(a) Decisions using base policy



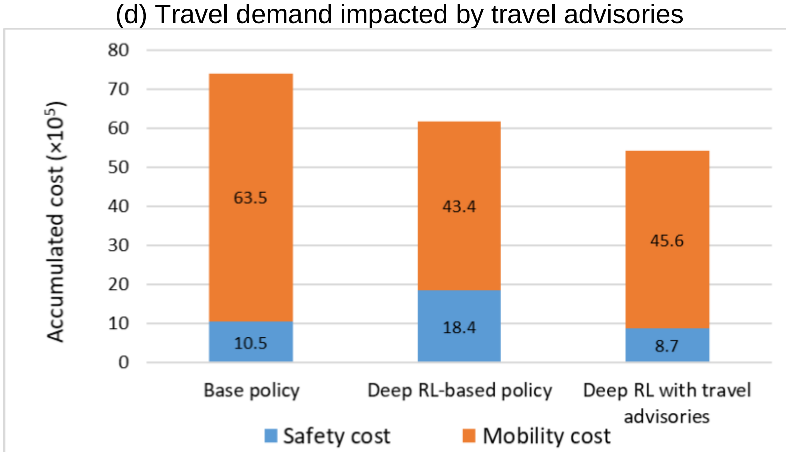
(b) Decisions using deep RL-based policy



(c) Decisions using deep RL-based policy with travel advisories

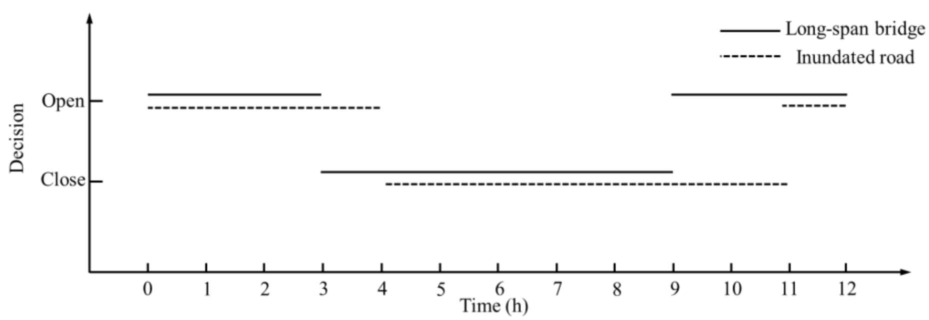


(d) Travel demand impacted by travel advisories

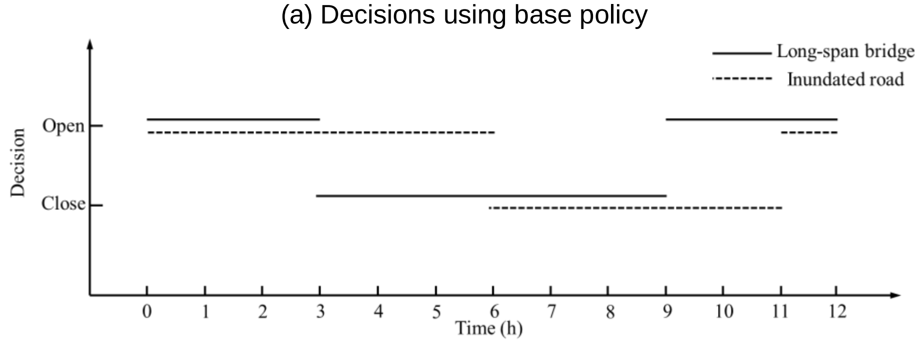


(e) Comparison of cost

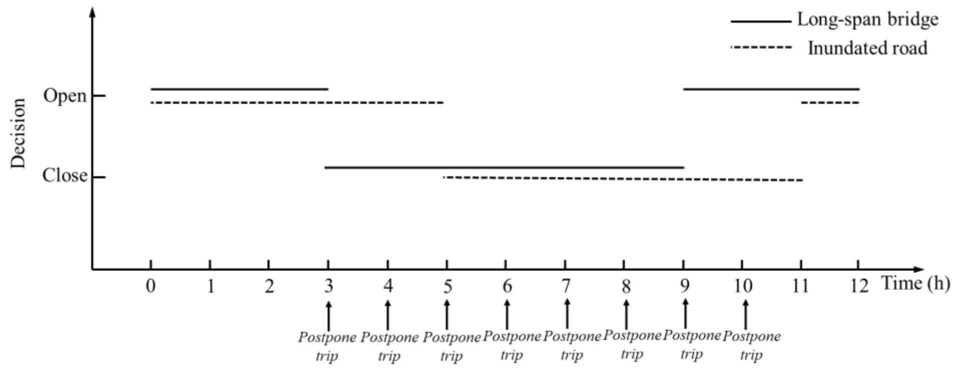
Figure 9. Simulation result under hurricane Case A



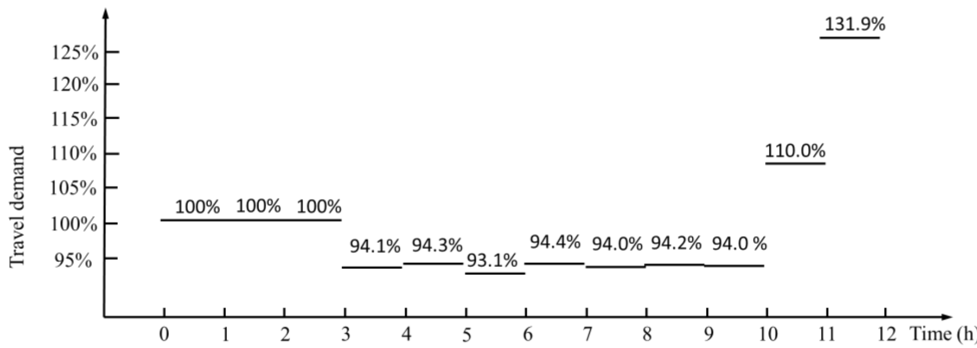
(a) Decisions using base policy



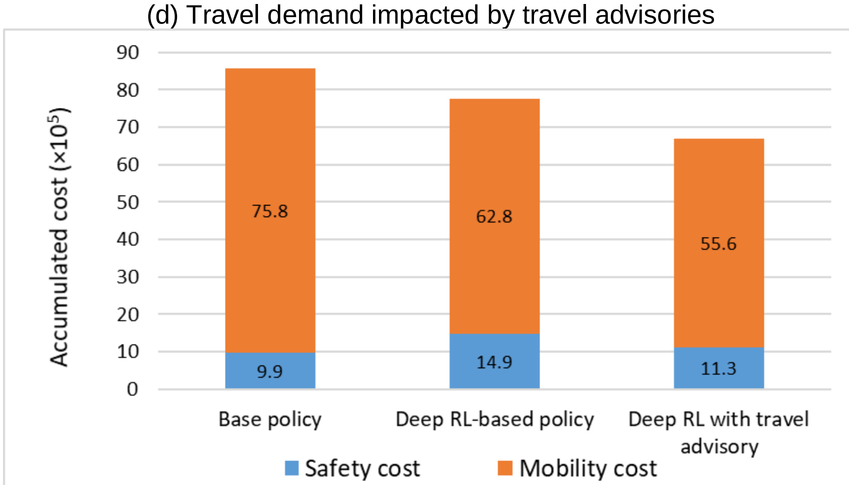
(b) Decisions using deep RL-based policy



(c) Decisions using deep RL-based policy with travel advisories



(d) Travel demand impacted by travel advisories



(e) Comparison of cost

Figure 10. Simulation result under hurricane Case B

CONCLUSIONS

For effective management of hurricane-impacted transportation infrastructures, this study proposes a deep reinforcement learning (RL)-based decision support system enhanced by intelligent travel advisories. A proof-of-concept example on a hypothetical traffic network under two hurricane events suggests the improved performance of the proposed scheme compared to conventional component-level decision-making and plain-vanilla deep RL-based approach. For the weak hurricane case with peak wind speed of 26m/s, the plain-vanilla deep RL-based policy reduces overall network-level cost by 16% at the expense of increasing the traffic-safety cost by 75% (compared to component-level policy), while travel advisory-enhanced deep RL-based scheme could reduce both overall network-level cost and traffic-safety cost by 27% and 17%, respectively (compared to component-level policy). For the strong hurricane case with peak wind speed of 29 m/s, the deep RL-based scheme with intelligent travel advisories leads to a higher reduction in network-level cost (22%) with a smaller increase (14%) in traffic-safety cost (compared to component-level policy), while the plain-vanilla deep RL-based approach obtains 9% reduction in overall network-level cost and 51% increase in traffic-safety cost (compared to component-level policy). These results demonstrate the good performance of the proposed travel advisory-enhanced deep RL-based scheme to maintain a low overall network-level cost without significantly increasing the traffic-safety cost.

REFERENCES

Ataei, N. and Padgett, J.E., 2013. Probabilistic modelling of bridge deck unseating during hurricane events. *Journal of Bridge Engineering*, 18(4), 275-286.

Baker, C.J., 1987. Measures to control vehicle movement at exposed sites during windy periods. *Journal of Wind Engineering and Industrial Aerodynamics*, 25(2), 151-161.

Bell, M.G. and Iida, Y., 1997. *Transportation network analysis*. Wiley, Chichester, UK.

Bureau of Public Roads, 1964. *Traffic assignment manual*. Washington DC.

Baker, C., 2015. Risk analysis of pedestrian and vehicle safety in windy environments. *Journal of Wind Engineering and Industrial Aerodynamics*, 147, 283-290.

Cools, M., Moons, E., Creemers, L. and Wets, G., 2010. Changes in travel behavior in response to weather conditions: do type of weather and trip purpose matter? *Transportation Research Record*, 2157(1), 22-28.

Fan, C., Zhang, C., Yahja, A. and Mostafavi, A., 2021. Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster management. *International Journal of Information Management*, 56, 102049.

FHWA, 2012, Best Practices for Road Weather Management. Report number: FHWA-HOP-12-046. https://ops.fhwa.dot.gov/publications/fhwahop12046/fhwahop12046.pdf

Gori, A., Gidaris, I., Elliott, J.R., Padgett, J., Loughran, K., Bedient, P., Panakkal, P. and Juan, A., 2020. Accessibility and Recovery Assessment of Houston's Roadway Network due to Fluvial Flooding during Hurricane Harvey. *Natural hazards review*, 21(2), 04020005.

Kim, J., Bae, J. and Hastak, M., 2018. Emergency information diffusion on online social media during storm Cindy in US. *International Journal of Information Management*, 40, 153-165.

Li, S., Snaiki, R. and Wu, T., 2021a. A knowledge-enhanced deep reinforcement learning-based shape optimizer for aerodynamic mitigation of wind-sensitive structures. *Computer-Aided Civil and Infrastructure Engineering* 733– 746.

Li, S., Snaiki, R. and Wu, T., 2021b. Active Simulation of Transient Wind Field in a Multiple-Fan Wind Tunnel via Deep Reinforcement Learning. *Journal of Engineering Mechanics* 147(9), 04021056.

Lu, H., Zhu, Y., Shi, K., Lv, Y., Shi, P. and Niu, Z., 2018. Using adverse weather data in social media to assist with city-level traffic situation awareness and alerting. *Applied Sciences*, 8(7), 1193.

Martinez-Rojas, M., del Carmen Pardo-Ferreira, M. and Rubio-Romero, J.C., 2018. Twitter as a tool for the management and analysis of emergency situations: A systematic literature review. *International Journal of Information Management*, 43, 196-208.

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G. and Petersen, S., 2015. Human-level control through deep reinforcement learning. *Nature*, 518(7540), 529-533.

Nozhati, S., Sarkale, Y., Chong, E.K. and Ellingwood, B.R., 2020. Optimal stochastic dynamic scheduling for managing community recovery from natural hazards. *Reliability Engineering & System Safety*, 193, 106627.

Pregnolato, M., Ford, A., Wilkinson, S.M. and Dawson, R.J., 2017. The impact of flooding on road transport: A depth-disruption function. *Transportation research part D: transport and environment*, 55, 67-81.

Snaiki, R. and Wu, T., 2017. A linear height-resolving wind field model for tropical cyclone boundary layer. *Journal of Wind Engineering and Industrial Aerodynamics*, 171, 248-260.

Snaiki, R. and Wu, T., 2018. An analytical framework for rapid estimate of rain rate during tropical cyclones. *Journal of Wind Engineering and Industrial Aerodynamics*, 174, 50-60.

Snaiki, R., Wu, T., Whittaker, A.S. and Atkinson, J.F., 2020. Hurricane wind and storm surge effects on coastal bridges under a changing climate. *Transportation Research Record*, 2674(6), 23-32.

Sutton, R.S. and Barto, A.G., 2018. *Reinforcement learning: an introduction*. MIT press.

Wardrop, J.G., 1952. Road paper. some theoretical aspects of road traffic research. *Proceedings of the institution of civil engineers*, 1(3), 325-362.

Watkins, C.J. and Dayan, P., 1992. Q-learning. *Machine learning*, 8(3-4), 279-292.

Wolshon, B., Urbina, E., Wilmot, C. and Levitan, M., 2005a. Review of policies and practices for hurricane evacuation. I: Transportation planning, preparedness, and response. *Natural hazards review*, 6(3), 129-142.

Wolshon, B., Urbina Hamilton, E., Levitan, M. and Wilmot, C., 2005b. Review of policies and practices for hurricane evacuation. II: Traffic operations, management, and control. *Natural Hazards Review*, 6(3),143-161.

Wu, T., Kareem, A. and Ge, Y., 2013a. Linear and nonlinear aeroelastic analysis frameworks for cable-supported bridges. *Nonlinear Dynamics*, 74(3), 487-516.

Wu, T., Kareem, A. and Li, S., 2013b. On the excitation mechanisms of rain–wind induced vibration of cables: Unsteady and hysteretic nonlinear features. *Journal of Wind Engineering and Industrial Aerodynamics*, 122, 83-95.

Zhou, Y. and Chen, S., 2015. Dynamic simulation of a long-span bridge-traffic system subjected to combined service and extreme loads. *Journal of Structural Engineering*, 141(9), 04014215.