Deep Reinforcement Learning-based Decision Support System for Transportation Infrastructure Management under Hurricane Events

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ABSTRACT: During hurricane weather and traffic conditions, stakeholders may need to make a series of decisions to close or restrict the traffic of vulnerable components in the transportation network (e.g., aerodynamics-sensitive long-span bridges, hydrodynamics-sensitive coastal bridges and inundation-sensitive road segments) for the balance of traffic safety and mobility. It is essentially a stochastic sequential decision problem and can be formulated as a Markov decision process. Hence, this study proposes a deep reinforcement learning (RL)-based decision support system for stakeholders to manage these critical components for the purpose of minimizing the network-level losses induced by hurricanes. The decision policy, i.e., the mapping from high-dimensional continuous traffic/weather information to traffic control decision, is represented by a deep neural network (DNN) while the optimal policy (represented by DNN weights) is obtained using the RL methodology. A numerical example of a hypothetical transportation network under hurricane conditions is utilized to demonstrate the good performance of this novel scheme.

Keywords: decision support system; transportation infrastructure; hurricanes; traffic; reinforcement learning; deep neural network.

1. INTRODUCTION
Hurricanes are among the most devastating natural hazards that result in enormous life losses and economic damages. It is imperative for stakeholders from government to private sectors to make a series of decisions for the purpose of reducing the hurricane-induced losses. A frequently encountered decision-making scenario during hurricanes involves travel risk mitigation and essential functionality maintenance of transportation network considering that both may be greatly impacted by hurricanes. For example, flexible long-span bridges may suffer from the high hurricane wind speed; low-lying coastal bridges with weak connection between substructure and superstructure are vulnerable to storm surges and waves; flooding-sensitive road segments are prone to inundations caused by heavy rainfall. Based on the hurricane weather and traffic condition, the stakeholders may need to make sequential decisions to close or restrict the traffic of these vulnerable components in the transportation network for the balance of traffic safety and mobility. Current decision-making practices for traffic under adverse weather conditions are mainly based on empirical judgements (e.g., road/bridge closure when wind/wave/surge/inundation exceeds certain threshold) and usually performed independently for each critical component (FHWA, 2012). These component-level decision policies may be unable to minimize the overall network-level impact considering the high interdependencies among these infrastructure components, which calls for improved decision support system to minimize the hurricane-induced losses on the transportation network.

This study proposes a novel decision support system based on deep reinforcement learning (RL).
Specifically, the sequential decision-making problem in the complex stochastic weather-traffic environment is 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. The optimal solution to a typical MDP problem could be obtained by techniques of dynamic programming (DP) or reinforcement learning (RL) (Sutton and Barto, 2018). It is noted that the existing weather-traffic system models are usually considered as “black-box” simulators involving several coupled modules from different disciplines (e.g., hurricane module, traffic network module and their interactions) with no close-form expressions. However, implementation of DP requires analytical system dynamics explicitly expressed in the form of state-transition probability. RL, on the other hand, can 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. Hence, it will be utilized in this study to obtain the optimal policy for hurricane-impacted traffic network. Furthermore, a deep neural network (DNN) is utilized to represent the decision policy, i.e., mapping from high-dimensional continuous weather/traffic information to the traffic control decisions while the optimal policy (represented by DNN weights) is obtained using the algorithm of deep Q learning (Mnih et al., 2015). For the proof of concept, a numerical example of a hypothetical transportation network under hurricane condition is utilized to demonstrate the good performance of the proposed scheme.

2. DEEP RL-BASED DECISION SUPPORT SYSTEM FOR A HURRICANE-IMPACTED TRANSPORTATION NETWORK

The management of transportation infrastructures under a hurricane event is a typical stochastic sequential decision problem, which could be formulated as a MPD. At time step $t$, the MDP state $s_t$ includes both the traffic $u_t$ and weather information $w_t$ for components in the traffic network, i.e., $s_t = [u_t, w_t]$, which may involve both current observation (denoted by superscript $o$) and future prediction (denoted by superscript $p$), i.e., $u_t = [u_t^o, u_{t+1}^p, \ldots, u_{t+h}^p]$ and $w_t = [w_t^o, w_{t+1}^p, \ldots, w_{t+h}^p]$ (where $h$ denotes the prediction horizon). The weather information could be obtained from the wind/wave/surge/inundation condition at critical locations using sensor measurements and/or prediction models. The traffic information, e.g., traffic flow on each road link, could come from the traffic surveillance and/or prediction systems. Based on current state $s_t = [u_t^o, u_{t+1}^p, \ldots, u_{t+h}^p, w_t^o, w_{t+1}^p, \ldots, w_{t+h}^p]$, stakeholders are required to take actions $a_t$, to decide to open or close each critical infrastructure component. At next time step $t+1$, the system states evolve to $s_{t+1} = [u_{t+1}^p, u_{t+2}^p, \ldots, u_{t+h+1}^p, w_{t+1}^o, w_{t+2}^o, \ldots, w_{t+h+1}^o]$ due to the change of hurricane weather, travel demand and the traffic reassignment caused by road opening/closure. It is noted that the analytical solutions of such complicated state-transition dynamics involving coupled hurricane-traffic interactions are currently not available. A reward $r_t$ (negative value of cost), i.e., $r_t = -f_m(u_{t+1}^o) - f_s(u_{t+1}^o, w_{t+1}^o)$, is received at each time step, which could be designed by stakeholders to consider both the cost from traffic mobility $f_m(u_{t+1}^o)$ and safety $f_s(u_{t+1}^o, w_{t+1}^o)$. The cost from traffic mobility $f_m(u_{t+1}^o)$ is related to the sum of travel time of all vehicles in the traffic network, while the safety-related cost $f_s(u_{t+1}^o, w_{t+1}^o)$ results from the traffic accidents in the adverse weather conditions, and hence depends on both traffic $u_{t+1}^o$ and weather condition $w_{t+1}^o$. The goal of decision-making for stakeholders is to maximize the expected cumulative reward $E(\sum_{k=0}^\infty \gamma^kr_{t+k})$, where $E$ is the expected value used to consider the uncertainties from hurricane weather, traffic condition and model predictions. The high interdependencies among different components makes the optimization problem very complicated.
In this study, the stochastic sequential decision problem formulated by MDP is approached by RL methodology empowered by DNN-based function approximations. As shown in Fig. 1, the RL environment is the transportation network under hurricane impact, which is simulated by coupled modules from different disciplines. Specifically, the hurricane wind is simulated using a height-resolving model, and the travel risk on the long-span bridge is represented by a vehicle accident fragility curve. Hurricane surge and wave are considered to be related to the wind intensity, and the surge/wave-induced coastal bridge damage is represented by a deck unseating fragility curve. Hurricane rainfall and hence the inundation is considered to be related to wind intensity, and the travel risk on the flooding-sensitive road segment is represented by a vehicle damage fragility curve. Considering the high-dimensional continuous state from weather/traffic information and the complex state-action relations, a DNN with powerful function approximation abilities is utilized to output the optimal traffic control actions (bridge/road closure or traffic flow restriction) for the critical infrastructures. During the training process, the DNN weights (the policy) are updated towards optimal values by the maximizing the user-defined reward using RL algorithm of deep Q learning (Mnih et al., 2015).

Figure 1. A deep RL-based decision support system for a hurricane-impacted transportation network

REFERENCES

