MODELING I-95 TO MEASURE THE RESILIENCE OF A HIGHWAY UNDER NORMAL TRAFFIC CONDITIONS

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ABSTRACT

Ground transportation systems are critical to the economy, safety, and quality of life of communities around the world. Thus, engineers and policy makers need to provide systems that are resilient to the impact of natural and man-made disasters. A resilience quantification framework plays a key role in this mission. This paper presents the first step to quantify the resilience of a road from a traffic operations perspective. This step consists of creating a traffic model of the road under study in order to assess the resilience of the system under normal and extreme conditions. In this case, a segment of I-95 in Virginia was studied. This paper illustrates the steps to create this model, and sets up the framework to simulate potential intrusions and interventions, and subsequently measure the resilience of the network.

Keywords: Ground Transportation, Resilience, Microscopic Traffic Modeling

INTRODUCTION

Ground transportation systems are critical to the economy, safety, and quality of life of communities around the world. According to the ASCE Report Card, forty-two percent (42%) of the urban highways in the United States have a traffic congestion problem [1]. Traffic congestion is caused by seven changing conditions: traffic incidents, work zones, weather, fluctuations in demand, special events, traffic control devices, and inadequate base capacity [2]. The inability of transportation systems to adapt to these changing conditions results in inadequate mobility and provision of services.

Civil engineers and policy makers have an obligation to build and renew transportation systems that can withstand the impact of changing conditions effectively. The ability of a system to resist, respond, and recover when faced with a disruptive event is defined as the *resilience* of the system. The need to increase the resilience of infrastructure systems in the United States has been recognized by renowned scholars, engineers, and government agencies [3-5]. However, many challenges still remain.

The National Academy of Sciences (NAS) identified the lack of a framework for measuring resilience as one of the current obstacles for implementing/improving infrastructure resilience [6]. This measuring framework is critical for identifying needs, monitoring changes, assessing mitigation strategies, and performing cost-benefit analysis. Another major challenge for implementing resilience improvement strategies is the monetary investment. To this point, it has being difficult to demonstrate that investing in resilience can have significant advantages. This is specially truth in the world of politics, where short-term result policies are typically favored over long-term result policies. Therefore, advocators of resilience need to provide analysis and prediction tools that help the general public and policy makers visualize the benefits of implementing resilience today to prepare for a better future.

This research addresses the need for the development of a framework to measure infrastructure resilience, specifically in the traffic engineering domain. The framework currently under development by the authors combines quantification metrics with a simulation approach. The simulations provides the capability of measuring resilience under typical or normal traffic conditions, as well as test multiple scenarios to assess the impact of potential intrusions and interventions in the system's resilience. This requires the creation of a traffic model to test the different scenarios and obtain the performance data necessary as input for the measuring framework. This paper illustrates the development of such traffic model by using a segment of I-95 in Virginia, and the microscopic traffic modeling tool called INTEGRATION©.

BACKGROUND

Previous Works on Measuring Ground Transportation Resilience

The quantification of resilience for infrastructure systems has been studied for more than one decade [7-11]. As a result, several models have been developed to measure the resilience of infrastructure. However, these models are designed to serve all types of systems, and thus, fail to adapt to the needs and characteristics of a particular type of infrastructure.

In the area of ground transportation systems, Murray-Tuite [12] identified ten dimensions of resilience, and examined the influence traffic assignment conditions on four of these dimensions. Subsequently, Heaslip et al. [13] combined a hierarchy of transportation needs and a Fuzzy Inference System (FIS) approach to convert qualitative measures of resilience into quantitative ones. This framework was later implemented by Urena Serulle et al. [14] in a case study of the resilience of the Santo Domingo, DR transportation network. Finally, Freckleton et al. [15] continued this line of work to define more in depth the selected resilience metrics. While these works explored the measurement of resilience in the context of ground transportation systems, they are limited to the interpretation of qualitative measures.

The literature shows that there is a need for further examination of quantification methods to measure the resilience of transportation networks. This paper presents the first step to examine the resilience of a road network from a traffic operations perspective. The proposed model measures resilience as a function of the operational performance of the network as it changes with respect to time and location. This approach is combined with the creation of a traffic model of the network under study, and the simulation of potential intrusions and interventions. Such simulation enables the prediction of the resilience of the network under likely intrusion scenarios, and the testing of potential interventions to assess how different strategies can help mitigate the impact of hazard events. This analysis can aid decision-making processes, as well as the creation of effective emergency management plans.

INTEGRATION© Software

The INTEGRATION© software was selected as the traffic modeling tool for this research. This trip-based model, developed by Van Aerde in the 1980s, combines microscopic details (e.g., car following, lane changing, and gap acceptance) with macroscopic features (e.g., traffic assignment, coordination delay, speed-flow relationships) to create a uniquely integrated model [16]. Other features include: the capability of capturing vehicle dynamics; the inclusion of energy, emissions, and safety models; and the flexibility for modeling various Intelligent Transportation System (ITS) applications.

As a microscopic tool, INTEGRATION© is capable of tracking vehicle movements from origin to destination in a deci-second resolution. This allows the analysis of dynamic phenomena such as shock waves, gap acceptance, and weaving. Also, the model is not restricted to hold constant departure rates, signal timing, incident severity, or traffic routings, which allow the attributes of the system to change on a continuous basis. Model outputs include several performance measures, such as average speed, travel time, vehicle delay, vehicle stops, fuel consumption, hydrocarbon, carbon monoxide, carbon dioxide, nitrous oxides emissions, and crash risk, among others.

Moreover, incidents and diversions can be incorporated at any time of the simulation. The software provides flexibility for modeling incidents of any duration and severity (e.g., blocking from 0 to 100% of the available capacity), modeling concurrent incidents at different locations, and modeling different incidents on the same location and time. These features are relevant for the simulation of intrusions in the network, in the context of this research.

METHODOLOGY

Creation of the I-95 Model

A 23.9-mile segment of Interstate 95 (I-95) in Virginia, between mile markers 149 to 173, was modeled for this paper. The model created in INTEGRATION© reflects the physical aspects of the network, as well as the normal traffic flow patterns during the morning peak hours when vehicles are traveling northbound towards the Washington, D.C. metro area. The segment extends Southwest of I-495 (also known as the Capital Beltway), and goes through the towns of Dumfries, Dale City, Woodbridge, Lorton, Newington and Springfield.

The geometry of the roadway segment was modeled by breaking down the network into links and nodes. The nodes created include origin and destination zones, as well as intermediate nodes used to break links when geometric characteristics or traffic stream parameters change. The links determine the roadway sections between any two nodes, and must contain the same characteristics. In this case, 113 nodes and 104 links were defined for the segment of I-95 under study. The information required to create the physical model of the network included: the node coordinates, link length, free-flow speed, saturation flow rate, jam density, and turn prohibitions, among others.

Once the physical characteristics of the network were modeled, the next step was to create an Origin-Destination (O-D) matrix that reflected the traffic flow on the network for the desired period of time. The selected period was 6:00 – 11:00 am during Wednesdays to reflect the morning peak traffic time, and subsequent recovery, during a regular working day. This step required the collection and processing of actual traffic data. The process of creating and calibrating the O-D matrix is described in the following section.

Estimation of the O-D Matrix

Origin-Destination (O-D) information can be collected by administering surveys and/or tracking vehicles. However, these methods are costly, labor intensive, and ineffective in capturing temporal changes in traffic behavior [17]. Thus, engineers are faced with the challenge of obtaining O-D traffic data that express accurately travel demand patterns without having to observe or measure them directly. To address this challenge, a synthetic O-D can be created using link traffic flow data recorded from loop detectors. Such loop detectors are often found in networks under surveillance, and typically collect volume (i.e., number of vehicles passing per unit time), occupancy (i.e., percentage of total time vehicles occupy the loop), and speed data.

For this research, loop detector data was obtained from the Virginia Department of Transportation (VDOT) for a period of 144 days (i.e., October 1, 2014 to February 22, 2015). The data set contained 51 detectors on the selected 23.9-mile segment of I-95. The northbound lanes were selected for this model due to higher quantity of data in this direction. The southbound direction and non-operating detectors were eliminated from the analysis.

Vehicle volume data was extracted from the data set to calculate the static O-D, a matrix that describes the movement of vehicles along the network over a long period of time. This static O-D dictates the maximum capacity, speeds at different levels of congestion, and the jam density in the network. The static O-D estimation requires the calculation of the average volume of vehicles per 15-minute period per weekday per detector. Once the data was processed for the segment under study, the average volume per detector was input into a tool called QUEENSOD®, which generated the O-D matrix required by INTEGRATION©.

Simulation of Normal Traffic Conditions

Once the nodes, links and O-D matrix were input into the model, the simulation was run to replicate the typical traffic conditions of the segment from 6:00 – 11:00 am during Wednesdays. This time period was selected to capture the behavior of the network during the morning peak hours of a regular working day, when the traffic in the northbound direction experiences the highest volume traveling towards the Washington, D.C. metro area.

Model Assumptions and Constraints

Several assumptions were made in creation of the model herewith presented. (1) The occurrence of random weather and incidents events does not affect the average performance of the system. The data collected for 144 days does not indicate when and where weather or incident event occurred, thus, it is challenging to stratify the data to not include such type of events. Instead, it is assumed that the impact of those events, if any, is diluted in the calculation of the average flow. (2) The model does not include routing. In this study, only one road segment was modeled, and thus, an assumption that all vehicles travel only through that road was made. In reality, drivers may choose to take alternative routes when traffic conditions diminish. The fact that no other parallel roads were modeled limits the drivers to only one route, and may impact the study by showing a performance lower than the actual performance experienced when drivers take alternative routes.

RESULTS AND DISCUSSION

The results of the simulation showed effectively the normal traffic conditions of the I-95 segment during the period under study. The performance of the road was examined using the average speed as parameter. The average speed profile obtained as result after analyzing the data is depicted in Figure 1, where the average speed of vehicles is plotted against the location in the network. The figure allows the reader to visualize how the performance of the road varies along the network, as the vehicles move from one section to another. The sections or towns can be observed in the secondary x-axis.

Moreover, the speed limit was also depicted in Figure 1 to show the comparison between the expected and actual performance. This comparison provides a straightforward method to visualize the location and magnitude of the loss in performance or *loss in resilience*. Two sections stand out as having the most dramatic loss in resilience during the period under study: Dale City (links 46-63) and Newington (links 91-101). Being able to identify and measure this loss in resilience is critical for assessing the overall resilience of the network and implementing effective mitigation strategies. In both cases, the sections are affected by the inadequate base capacity of the road when faced with the normal traffic conditions of the morning peak hours. The sections are impacted by changes in number of lanes and high volume of vehicles entering and/or exiting the interstate at these locations. Understanding how the resilience changes along the network and the issues that trigger the loss in resilience is essential for improving the system.

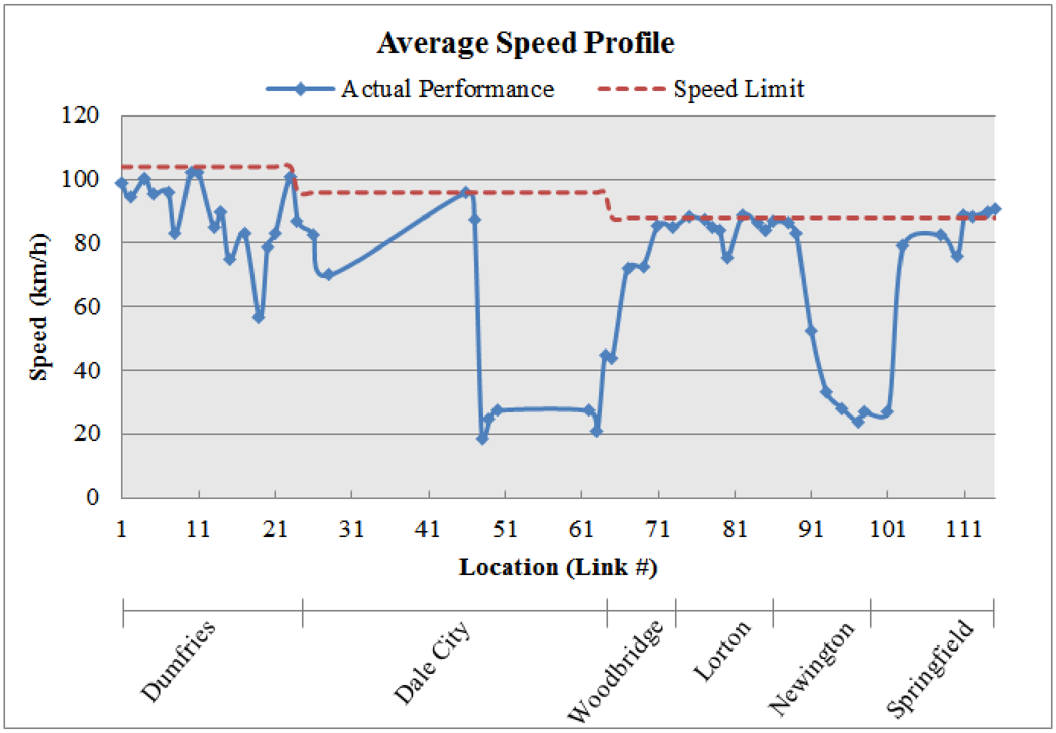

Figure 1: Average Speed Profile for I-95 Segment between 6-11 am from Oct-01-14 to Feb-22-15

CONCLUSION

This paper aimed at illustrating the traffic modeling and simulation approach that will serve as input to a resilience measuring framework that is currently under development by the authors. Such measuring framework is critical to implement resilience improvement strategies for transportation systems. The framework will not only be capable of measuring resilience under normal traffic conditions, but can also be used to: (1) predict the impact of multiple hazards on the road operations, and (2) predict the impact of highway management interventions in the improvement of the system resilience.

A model of a segment of I-95 near the Washington, D. C. was created for this paper. Normal traffic conditions were simulated for the morning peak hours from 6:00 – 11:00 am on a typical working day. The results show how the performance of the system, illustrated through the average speed, changed along the network. Locations with the highest loss in resilience were identified from this analysis, and will become the areas of interest for testing resilience mitigation strategies in the future.

Future research will examine the impact intrusions and interventions on the network. Three intrusions will be tested on I-95: traffic incidents, work zones, and weather. Similarly, several interventions will be tested, including variable speed limits, ramp meters, and shoulder lane use. Different scenarios will be designed to assess the impact of intrusions and interventions individually and occurring simultaneously.

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