Link Criticality Evaluation for Day-to-Day Degradable Transportation Networks

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ABSTRACT
Link criticality evaluation is an important problem for public officials to make hazard mitigation planning. However, this type of analysis presents numerous challenges in terms of accurately capturing the impacts of highly stochastic hazard events. This study proposes an analytical framework and an efficient solution procedure for link criticality evaluation, which considers the impact of day-to-day degradable transportation network conditions. Link capacity is considered as a multi-status variable, and a sampling technique is used to generate realizations of transportation network capacity values. With different capacity realizations, traffic demand is repeatedly assigned on the regional planning model network, and the assignment results are measured with multiple criteria and analyzed using several statistical indices. A case study based on a portion of the New Jersey roadway network is presented to verify the proposed approach.
INTRODUCTION

Identification of the critical links in a transportation network is an important part of transportation network vulnerability analysis. This problem is concerned with finding the links that result in severe deteriorations of network performance (e.g. total users’ travel time), when degradable. In the case of a specific application for transportation facilities assessment, most studies use an enumeration method (complete sampling), that sets scenarios which each assume a certain link is degradable. The links which cause severe network performance deteriorations are identified as the critical links.

When considering link degradation levels, past studies normally assume binary status: fail or not. This assumption is reasonable under emergency situations, such as earthquakes or hurricanes, however it is not suitable for daily traffic conditions (1). Daily uncertain events may simultaneously result in different links degrading at multiple levels. In other words, the operational capacity of a link is a continuous status, and degradation might happen simultaneously for different links under daily transportation network conditions. Thus, it is necessary to adopt a more practical approach to capture link criticality for day-to-day degradable transportation networks, due to the occurrence of various hazard events.

The main objective of this study is to detect and rank critical links considering degradable transportation networks under the risks of daily hazard events. We propose an analytical framework incorporating realistic, risk-related datasets with regional transportation planning model. In order to represent day-to-day transportation network conditions, the traditional regional planning model is extended by considering link capacities as variables with certain distributions. The distributions of link capacities are calculated through the combination of frequency of risks and corresponding roadway capacity reductions. For link criticality analysis, firstly, we repeatedly run the traffic assignment procedure in the regional planning model with different network capacity realizations. Then, a GIS-based interactive computer tool, developed for the evaluation and analysis of full cost of highway transportation, is used to calculate total system cost. Finally, based on the calculated costs, the critical links are detected and ranked in terms of following statistical indices: Rank Correlation Coefficients (RCCs), Standardized Rank Regression Coefficients (SRRCs), and Partial Rank Correlation Coefficients (PRCCs).

Several features distinguish this study from previous ones. Firstly, the roadway capacities in degradable transportation networks are considered as multi-status but not as binary status, as in the previous studies. Through sampling technique, each sample realization can be interpreted as one daily network capacity condition. Secondly, we measure the total cost with different performance measures via a GIS-based interactive computer tool that calculated total network travel costs, not as general total system travel time. Finally, three statistical indices are used for measuring criticality in this study, instead of Volume-to-Capacity ratio (V/C). V/C ratio is commonly used as a criticality measure with full capacity assumption. However when considering daily hazard events, it’s not a proper measure due to day-to-day dynamic transportation network conditions.

The paper is organized as follows: Section 2 reviews the literature related with critical-link determination in a degradable transportation network and multi-criteria measures in decision support systems. Section 3 presents the methodology, including mathematical formulation, sampling-based method, the GIS-based interactive computer tool for calculation of costs and sensitivity analysis measures. In Section 4, a case study with a portion of the New Jersey roadway network is presented. The final section provides conclusions and opportunities for future research.
LITERATURE REVIEW

The problem addressed in this study is related with previous theoretical work on the most vital arc or edge problem. In detail, the problem is finding the arc or edge that on its removal results in maximum deterioration of network performance. The solution methods include graph theory and game theory. In graph theory, a general performance measure can be the increase of shortest path length (2–3). The studies formulated the most vital arcs problem as determination of the subset of arcs whose removal from the network resulted in the greatest increase in the shortest path length. The measure of the performance of a network in (4) was the increase of the distance between the origin nodes and sink nodes in a maximum flow graph. While game theory approach(5) considered the situation where a network “spoiler” seeks to disrupt the network to maximize user costs by choosing the link that causes the maximum impact, while users try to minimize their costs by adjusting their routes according to the expected link costs. The results of the game were therefore worst-case link failure probabilities, which could be used to find the upper-bound impact of link degradation. Applications of this approach were described in (6) and (7).

For the specific application in the assessment of transportation facilities, most studies use bi-level formulations to solve the problem. At the lower level, assign vehicles to achieve the goal of user equilibrium or system optimality; at the upper level, critical links that maximize network performance deteriorations as a result of their removal are identified. The procedure mainly relates with three issues: the assignment methodology, performance measure and Decision Support Systems (DSS).

The assignment methodology can be generally categorized as either static or dynamic traffic assignment. Static assignment assumes that traffic is in a steady status, and the time to traverse a link depends only on the number of vehicles on that link. Because of its simple mathematical formulation and solution procedure, static assignment is widely applied for link criticality evaluation on a regional network scale. Dynamic assignment can successfully represent the time-varying nature of the congestion during different times of the day, and help to understand travelers’ responses to time-varying transportation system operations. However, compared with static assignment, dynamic assignment requires more data-support and computation cost. Thus, dynamic assignment is more suitable for evaluating simple networks or arterial analysis considering users’ behavior.

Performance measure can be separated into two categories: accessibility and economic measures. Accessibility refers to the ‘ease’ of reaching opportunities for activities and services, and can be used to assess the performance of an urban transportation system (8–10). Economic measures refer to the cost of disruption due to the degradable critical links, such as travel time (11–16), environment (17) and network efficiency (18). In detail, alternative definitions and measures are summarized in (19–20).

DSS based on multi-criteria measures in transportation infrastructure evaluation have been investigated in various areas, such as infrastructure maintenance and management (21–22), highway safety and incident/accident management (23–24). The common features in the previous DSS can be categorized as follows: the characteristics of uncertainties, performance measure, qualitative nature of sub-system components and the general system size. Because of system complexity and insufficient dataset, knowledge-based expert systems are commonly used for optimized solutions. A recent application of DSS in critical civil infrastructure management for disasters can be seen in (25).
RESEARCH METHODOLOGY
Mathematical Formulation

The general procedure of a regional transportation planning model includes four steps: trip generation, trip distribution, model split and traffic assignment. Through the first three steps, the total number of travelers for each transportation mode (auto, transit, etc.) can be predicted. Static traffic assignment can then be used to assign the predicted demand onto the transportation network. In static traffic assignment, traffic demand between origins and destinations is generally assumed as an input from previous three steps.

Static traffic assignment has found significant applications since (26). Typically, two types of traffic assignment can be performed: User Equilibrium (UE) - which assumes that users reach equilibrium when they cannot improve their travel time by switching to alternate routes, and System Optimum (SO) - which estimates link flows based on some system-wide objective (e.g., minimization of travel time). This static network analysis is generally based on mean values, such as travel time, travel distance or level of congestion. However, for the critical link analysis under the assumption of the possibility of certain types of disasters, a probabilistic approach is needed. From (27) the “deterministic” formulation of each of the above approaches is as follows:

\[
SO: \quad \text{Min} \sum_a x_a c_a(x_a) \quad \text{or UE: } \quad \text{Min} \int_0^{x_a} c_a(\omega) d\omega
\]

\[
s.t.
\]

\[
\sum_k h_k^{rs} = q_{rs} \quad \forall r, s
\]

\[
h_k^{rs} \geq 0 \quad \forall r, s
\]

\[
x_a = \sum_r \sum_s \sum_a h_k^{rs} \delta_{ak} \quad \forall a
\]

Where \(q_{rs}\) is the OD flow from origin \(r\) to the destination \(s\), \(h_k^{rs}\) is the flow on the path \(k\) from \(r\) to \(s\), \(\delta_{ak}\) is a binary value indicating that link \(a\) exists on path \(k\) between \(r\) and \(s\), \(x_a\) is the flow on link \(a\), and \(c_a\) is the cost of link \(a\).

Traditionally, the adequacy of a road network is evaluated based on deterministic network capacity and origin-destination demands. In order to model the impact of uncertain events on link capacity, sensor data can be used (28). When sensor data is unavailable, the link status may be represented by a theoretical probability function of the following form:

\[
C_{iv} = f(S_{i1}, S_{i2}, \ldots, S_{im})
\]

Where \(C_{iv}\) is the real capacity of link \(i\) in the presence of certain uncertain events namely, \(S_{i1}, S_{i2}, \ldots, S_{im}\). For example, considering accidents and extreme weather conditions, the link capacity can be simply represented as:

\[
C_{iv} = (1 - \alpha_{ia})(1 - \alpha_{iw})C_i
\]

Where \(C_i\) is the recommended link capacity value in HCM 2000 (29), \(\alpha_{ia}\) and \(\alpha_{iw}\) are capacity reduction coefficients of accident and weather status, respectively. The link capacity distribution can be obtained by repeatedly calculating equation (3) for different days.
Sampling-Based Method for Representing Effect of Stochastic Hazard Events

Suppose for a network with $m$ links, the network capacity can be formulated as a variable vector $\xi = (\xi_1, \xi_2, \ldots, \xi_m)$. Each item $\xi_i$ represents a certain link capacity with a probability distribution $p_i$. We can generate a network capacity as a variable vector with certain realizations, and then propagate the samples through the analysis to produce the mapping $[\xi, F(x, \xi)]$. $F$ is the measure function, such as objective function in equation (1). However, the mapping procedure is usually the most computationally demanding part of a sampling-based uncertainty and sensitivity analysis. For example, a network with 200 links and 3 link status, the total number of scenarios is $3^{200}$. It is not thus computationally possible to solve the formulation given in (1) for all capacity realizations.

However we can use variance reduction sampling techniques (31) to obtain approximate solutions by selecting subsets of the set $(\xi_1, \xi_2, \ldots, \xi_k)$. This approximate solution approach, known as a Sample-Average Approximation (SAA) of $f(x)$, is then minimized by using a deterministic optimization algorithm. The detailed steps of SAA technique employed in this study can be seen in FIGURE 1. The detailed behavior of this technique and its application can be seen in (30) and (31).

It should be noted that because static assignment is used for each realization of capacity reduction, it assumes that users have perfect information about the current network condition. Moreover, although in reality it may depend on network topology (e.g. series or parallel links), the capacity of any pair of links are assumed independently distributed in this study. Our consideration is that the proposed framework is mainly used for regional planning. The mathematical formulation, data collection process and analysis are all on a macroscopic level. In addition, the incorporation of link correlation in the proposed framework may bring more questions, such as how many upstream links need to be considered, and how to set all the values of degradable factor for all those links. Currently, macroscopic data are not sufficient to answer such questions.

FIGURE 1 Representation of SAA Solution Steps
GIS-Based Multi-Criteria Cost Estimation Tool

GIS-based multi-criteria cost estimation tool, which is named as Advanced Software for Statewide Integrated Sustainable Transportation System: Monitoring and Evaluation (ASSIST-ME), is a computer program developed by Ozbay et al. (32). ASSIST-ME employs ArcGIS in the Visual Basic .NET environment to visualize and process very large amount of model and sensor data for a given transportation network. It calculates direct and indirect transportation related link-based or O-D based trip costs using the output of the regional planning model. O-D based trip cost is calculated using the constrained k-shortest path algorithm implemented in C programming language. Link-based costs are calculated for a selected region (e.g. county) or network-wide. In order to calculate the total network costs, link-based cost estimation functionality of ASSIST-ME is used in this study.

The cost categories used in this study are: vehicle-operating, travel time and congestion, accident, air-pollution, noise, and maintenance costs. Each cost function was estimated in (33~34) using data obtained from New Jersey Department of Transportation (NJDOT) and other state and national sources. These cost functions are presented in TABLE 1. It should be noted that data on vehicle operation cost, accident cost, and infrastructure cost are NJ-specific, whereas congestion and environmental costs are adopted from relevant studies in the literature. The parameters of the cost functions are modified to reflect NJ-specific conditions.

<table>
<thead>
<tr>
<th>TABLE 1 Cost Function in ASSIST-ME (32~34)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost</td>
</tr>
<tr>
<td>Operation</td>
</tr>
<tr>
<td>Congestion</td>
</tr>
<tr>
<td>Accident</td>
</tr>
<tr>
<td>Air pollution</td>
</tr>
<tr>
<td>Noise</td>
</tr>
<tr>
<td>Maintenance</td>
</tr>
</tbody>
</table>
Sensitivity Analysis

Rank Transformation Technique

A number of statistical indices which can be used along with SAA procedure are briefly summarized in (30). For a linear relationship, the common statistical indices are correlation coefficients (CC), standardized regression coefficients (SRC), and partial correlation coefficients (PCC). All three indices can provide a criticality strength of linear relationship between $\xi$ and $F(x, \xi)$. For capturing a nonlinear relationship, rank transformation (35) is a well-known technique proved to perform efficiently by (30). By using rank transformation, input data $\xi$ and output result $F(x, \xi)$ are replaced with their corresponding ranks so that the linear relationship measures can be used. For each capacity realization $\xi_{ij}$, $i$ is the sample number and $j$ is the link number. An example rank transformation scheme can be seen in FIGURE 2. A detailed discussion about rank transformation in the context of sensitivity analysis can be found in (35).

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{Rank Transformation Technique with Criticality Measures}
\end{figure}

Criticality Measures

In this study, sensitivity results obtained based on the following criticality measures borrowed from (30) are illustrated and compared. These are Rank Correlation Coefficients (RCCs), Standardized Rank Regression Coefficients (SRRCs), and Partial Rank Correlation Coefficients (PRCCs).
RCCs

RCCs provides a measure of the strength of the linear relationship between ranked $\xi$ and $F(x, \xi)$. The measure can be mathematically expressed as follows:

$$c(\xi_j, F) = \frac{\sum_{i=1}^{m} (\xi_j - \bar{\xi})(F_i - \bar{F})}{\left(\sum_{i=1}^{m} (\xi_j - \bar{\xi})^2\right)^{1/2} \left(\sum_{i=1}^{m} (F_i - \bar{F})^2\right)^{1/2}}$$

(4)

Where $\bar{\xi} = \sum_{i=1}^{m} \xi_j / m$ and $\bar{F} = \sum_{i=1}^{m} F_i / m$, $m$ is the sampling size.

SRRCs

Regression analysis in this study is formulated as linear models of the following form:

$$\hat{F} = b_0 + \sum_{j=1}^{m} b_j \xi_j$$

(5)

The regression coefficients in equation (5) are determined such that the sums of equation (6) and (7) are minimized, respectively.

$$\sum_{i=1}^{m} (F_i - \hat{F})^2 = \sum_{i=1}^{m} [F_i - (b_0 + b_j \xi_j)]^2$$

(6)

$$\sum_{i=1}^{m} (F_i - \hat{\xi}_j)^2 = \sum_{i=1}^{m} [F_i - (b_0 + \sum_{j=1}^{m} b_j \xi_j)]^2$$

(7)

PRCCs

The PRCCs equation is related to RCCs equation. Firstly we formulate two regression models:

$$\hat{\xi}_j = c_0 + \sum_{p=1, p \neq j}^{m} c_p \xi_p$$

and

$$\hat{F}_j = b_0 + \sum_{p=1, p \neq j}^{m} b_p \xi_p$$

(8)

Then use the new variables $\hat{\xi}_j - \hat{\xi}_j$ and $F - \hat{F}$ to calculate RCC by equation (4). In other words, PRCCs between $\xi_j$ and $F$ is the RCCs between $\xi_j - \hat{\xi}_j$ and $F - \hat{F}$.

CASE STUDY

Regional Planning Model and Network Description

A case study is performed on the network of Northern New Jersey. The roadway network includes densely-populated, congested locations. The regional planning model, North Jersey Regional Transportation Model-Enhanced (NJRTM-E, 36), is used to estimate the traffic flows on the network. NJRTM-E is a four-step transportation planning model currently used by the North Jersey Transportation Planning Authority (NJTPA). Four separate networks are run for the time periods in the model: AM Peak (6:00am-9:00am), Midday (9:00am-3:00pm), PM Peak (3:00pm-6:00pm), and Night (6:00pm-9:00am). The model includes a detailed highway network with 6.5 million residents and 23,000 miles of highway network, which includes 2,553 zones, 21,740 nodes and 43,709 links.

Based on the NJRTM-E model, it is possible to estimate the transportation costs via ASSIST-ME under possible roadway capacities combinations. In this case study, seven major roadways located in Union and Essex counties are selected for analysis in the PM Peak time period. The impact of weather and accidents on roadway capacity are considered. Detailed information about roadway sections can be seen in TABLE 2.
TABLE 2 Information for the Roadway Sections

<table>
<thead>
<tr>
<th>Link No.</th>
<th>Name</th>
<th>County</th>
<th>Road Type</th>
<th>Milepost</th>
<th>No. Acc*</th>
<th>V/C Ratio**</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>I-78</td>
<td>Union, Essex</td>
<td>Interstate Highway</td>
<td>55-60</td>
<td>69</td>
<td>1.05</td>
</tr>
<tr>
<td>2</td>
<td>U.S. 1&amp;9</td>
<td>Union, Essex</td>
<td>U.S. Highway</td>
<td>45-48</td>
<td>33</td>
<td>1.09</td>
</tr>
<tr>
<td>3</td>
<td>U.S. 1&amp;9</td>
<td>Union</td>
<td>U.S. Highway</td>
<td>42-45</td>
<td>42</td>
<td>0.87</td>
</tr>
<tr>
<td>4</td>
<td>I-95</td>
<td>Union</td>
<td>Interstate Highway</td>
<td>52-55</td>
<td>51</td>
<td>1.14</td>
</tr>
<tr>
<td>5</td>
<td>I-95</td>
<td>Union, Essex</td>
<td>Interstate Highway</td>
<td>55-58</td>
<td>30</td>
<td>1.06</td>
</tr>
<tr>
<td>6</td>
<td>NJ-27</td>
<td>Union</td>
<td>Regional Highway</td>
<td>31-34</td>
<td>68</td>
<td>0.88</td>
</tr>
<tr>
<td>7</td>
<td>NJ-27</td>
<td>Union, Essex</td>
<td>Regional Highway</td>
<td>34-38</td>
<td>31</td>
<td>0.82</td>
</tr>
</tbody>
</table>

*The value obtained from local transportation agencies (38), PM peak period (3PM-6PM)
**The value obtained from the result of PM peak period network assignment result in NJRTM-E (36)

Analysis Approach

One of the most frequently used sampling methods, Latin Hypercube Sampling (LHS), is used as the sampling technique in SAA. A detailed analysis of the convergence and approximation accuracy properties of LHS can be found in (37). The full costs calculated by ASSIST-ME are used as the performance measure. The general steps of the proposed methodology are as follows:

**Step 1: Collect historical weather information and accident frequencies**

Weather information is obtained from weather stations through national climatic data center (www.ncdc.noaa.gov). The weather information includes precipitation under normal and extreme conditions such as rain or snow. The roadway accident frequency is obtained from the local transportation agencies (38). The detailed accident records include occurrence time, roadway direction, and position by milepost. In this study, we only collect and analyze the datasets for weekdays.

**Step 2: Generate actual link capacity distributions**

Incorporated with the weather and accident database, the actual link capacity distributions are calculated by aforementioned equations (2) and (3) using roadway accident data (38) and weather data. The roadway capacity reduction under different weather and accident conditions are based on the information from the literature (39–41).

**Step 3: Obtain different samples and calculate the performance cost for each sample**

By using LHS method, 20 different network capacity realizations are sampled. Then, the regional planning model NJRTM-E is repeatedly used to assign the demand matrix with these different network capacity realizations. Finally, we use ASSIST-ME to calculate the total costs based on the network assignment results.

**Step 4: Detect and rank critical links**

We treat the network capacity realizations as inputs, and the total costs calculated by ASSIST-ME as outputs. Then we rank the inputs and outputs by rank transformation technique respectively, and detect and rank the critical links using various criticality measures.

Capacity Reduction

Impact of Accidents

HCM 2000 (29) summarized related studies and identified some guidelines for capacity reduction due to accidents or incidents such as vehicle breakdowns. The proportion of capacity available under accident or incident conditions (number of lanes blocked) were summarized and analyzed, which can be seen in TABLE 3.
TABLE 3 Freeway Segment Capacity Available Under Incident Conditions

<table>
<thead>
<tr>
<th>Number of Freeway Lanes by Direction</th>
<th>Shoulder Disablement</th>
<th>Shoulder Accident</th>
<th>One Lane Blocked</th>
<th>Two Lanes Blocks</th>
<th>Three Lanes Blocked</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.95</td>
<td>0.81</td>
<td>0.35</td>
<td>0.00</td>
<td>N/A</td>
</tr>
<tr>
<td>3</td>
<td>0.99</td>
<td>0.83</td>
<td>0.49</td>
<td>0.17</td>
<td>0.00</td>
</tr>
<tr>
<td>4</td>
<td>0.99</td>
<td>0.85</td>
<td>0.58</td>
<td>0.25</td>
<td>0.13</td>
</tr>
<tr>
<td>5</td>
<td>0.99</td>
<td>0.87</td>
<td>0.65</td>
<td>0.40</td>
<td>0.20</td>
</tr>
<tr>
<td>6</td>
<td>0.99</td>
<td>0.89</td>
<td>0.71</td>
<td>0.50</td>
<td>0.26</td>
</tr>
<tr>
<td>7</td>
<td>0.99</td>
<td>0.91</td>
<td>0.75</td>
<td>0.57</td>
<td>0.36</td>
</tr>
<tr>
<td>8</td>
<td>0.99</td>
<td>0.93</td>
<td>0.78</td>
<td>0.63</td>
<td>0.41</td>
</tr>
</tbody>
</table>

N/A - not applicable
Source: HCM 2000 (27)

Impact of Extreme Weather
Extreme weather refers to rain, snow, fog and other adverse weather conditions. Recent research (39–41) emphasized the importance of extreme weather intensity in terms of capacity reduction. The weather reduction factors for this case study can be seen in TABLE 4.

TABLE 4 Weather Reduction Factors Used for the Case Study

<table>
<thead>
<tr>
<th>Weather Condition</th>
<th>Trace (&lt;0.01*)</th>
<th>Light [0.01-0.25]</th>
<th>Heavy (&gt;0.25)</th>
<th>Clear [0.01,0.25]</th>
<th>Others (&gt;0.25)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rain</td>
<td>1-5%</td>
<td>5%-10%</td>
<td>10%-15%</td>
<td>5%-10%</td>
<td>10%-15%</td>
</tr>
<tr>
<td>Snow</td>
<td>5%-10%</td>
<td>10%-15%</td>
<td>5%-10%</td>
<td>10%-15%</td>
<td>15%-20%</td>
</tr>
</tbody>
</table>

* Represented by hourly precipitation

Results and Discussions
Because of the data collection requirements of accident frequencies, it is not practical to obtain such data for short roadway segments that are frequently encountered in the NJTRM-E network model. Moreover, in terms of mathematical formulation and sample-based solution method, the link conditions are assumed to be independent. However in reality, the capacity of adjacent links may be correlated with each other. Thus, when calculating the risk-related capacity reductions, we attempt to combine several short-distance links in order to incorporate the link capacity correlation observed in reality, and also make the network size practical for realistic accident data collection and processing.

The first interesting observation is the characteristics of daily roadway capacity when considering both weather and accident impacts. Among the seven selected routes, in general around 20% of weekdays’ roadway capacities are affected by weather and accident conditions. 5% of weekdays’ roadway capacities are reduced by more than 15% of the average capacity settings. Most of these severe capacity degradations are caused by accidents. Moreover, we also tried to fit the daily roadway capacities in order to find common probability distributions. However, the daily capacity distributions vary for different roadway sections, and no theoretical distributions can be easily fit. An example of the probability density of available roadway capacity can be seen in FIGURE 3.
FIGURE 3 An Example of the Probability Density of Available Roadway Capacity

Note that the link criticality is defined as the links that have significant influence on transportation network performance degradation. The criticality measures (RCCs, SRRCs, and PRCCs) are statistical indices to analyze the relationship between input (link capacity realizations) and output, which is calculated based on the assigned result and ASSIST-ME software tool. The detailed critical link detection and ranking can be seen in TABLE 5. The p-value is used to test the null hypothesis statuses that no relationship exists between the involved variables, versus the alternative of the probability that the strong linear relationship exists. The lower p-value means the test results show that the results are less likely to agree with the null hypothesis. In this study, the facility with the lower p-value is the more significant or critical link in the degradable transportation network.

TABLE 5 Critical Link Detection and Ranking in Case Study Network

<table>
<thead>
<tr>
<th>Link No.</th>
<th>Name</th>
<th>RCC</th>
<th>SRRC</th>
<th>PRCC</th>
<th>No. Acc</th>
<th>V/C Rank*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>p-value</td>
<td>Rank</td>
<td>p-value</td>
<td>Rank</td>
<td>p-value</td>
</tr>
<tr>
<td>4</td>
<td>I-95</td>
<td>0.0000</td>
<td>1</td>
<td>0.0000</td>
<td>1</td>
<td>0.0000</td>
</tr>
<tr>
<td>6</td>
<td>NJ-27</td>
<td>0.0031</td>
<td>2</td>
<td>0.0000</td>
<td>2</td>
<td>0.0149</td>
</tr>
<tr>
<td>1</td>
<td>I-78</td>
<td>0.0048</td>
<td>3</td>
<td>0.0001</td>
<td>3</td>
<td>0.1435</td>
</tr>
<tr>
<td>2</td>
<td>U.S.1&amp;9</td>
<td>0.0059</td>
<td>4</td>
<td>0.0007</td>
<td>4</td>
<td>0.2356</td>
</tr>
<tr>
<td>5</td>
<td>I-95</td>
<td>0.0087</td>
<td>5</td>
<td>0.0013</td>
<td>5</td>
<td>0.3347</td>
</tr>
<tr>
<td>3</td>
<td>U.S.1&amp;9</td>
<td>0.0132</td>
<td>6</td>
<td>0.0017</td>
<td>6</td>
<td>0.3159</td>
</tr>
<tr>
<td>7</td>
<td>NJ-27</td>
<td>0.0347</td>
<td>7</td>
<td>0.0036</td>
<td>7</td>
<td>0.5770</td>
</tr>
</tbody>
</table>

* Rank in descending order according with the values in Table 2.
Our results demonstrate that the critical links detected by the proposed methodology are correlated with the V/C ratios. TABLE 5 shows that most of the links with high V/C ratio are critical links, such as I-95 and I-78. This is a plausible finding because a high level of usage under normal conditions may imply a potentially significant loss for a degradation scenario. For example, under extreme weather conditions, the interstate highway system may have more significant influence on total performance degradation, compared with regional local streets. Moreover, statistics (29) also indicate that the frequency of accidents/incidents also correlate with link-specific Average Annual Daily Traffic (AADT) and V/C ratios.

However, it is also observed that not all the links with high V/C ratio are consistent with the results presented in TABLE 5. An illustrative example is one roadway segment of NJ-27 (Link No. 6). The historical accident rate is high for this link but it has a relatively low V/C ratio. The most likely explanation is that this result may be due to the combination of various causes of possible link degradations. Travelers may switch to paths which include local links under the user equilibrium assumption. Especially for congested traffic conditions, when a number of travelers drive out of a dense urban area, even a partial capacity reduction of a local link (due to an incident or extreme weather) may significantly degrade the roadway network performance. This is the general criticism by previous studies (1, 12~13). The well-known and widely used performance measures such as the V/C ratios are not adequate for planning and maintenance approaches, because it is inherently localized and static in nature (1).

In this study, our main concern is to propose a comprehensive framework that defines a way to incorporate various causes of network capacity degradation into link criticality analysis. The case study is an example employed to show how the proposed framework would work. Although the case study results may be restricted by the regional setting, they still shed some light on the link criticality analysis. Firstly, the proposed framework introduces a novel way to combine different degradation factors into the link criticality analysis via regional planning model. The results shown in TABLE 5 can be considered as a comprehensive link criticality evaluation analysis considering the combination of network-wide influence of two degradation factors namely, extreme weather conditions and incident/accidents. As discussed above, single and localized performance measures are not adequate for transportation planners confronting with a complex transportation system because they may lead to biased results. Second, with increasing number of sensors being deployed in the real-world, this case study is also a demonstration to combine all of the possible empirical data sources together to offer the decision makers more realistic and reliable link criticality results.

CONCLUSION AND FUTURE RESEARCH

In this study, a novel analytical framework and efficient solution procedure are proposed for the detection and ranking of critical links considering day-to-day degradable transportation network conditions. Sample-Average Approximation (SAA) methodology is used for capturing network capacity uncertainty and solving the formulated stochastic mathematical problem. The difference between the proposed methodology and earlier related work is that rather than using a scenario analysis based on simple assumption of binary status (fail or not) of a link capacity, the proposed framework can be used for capturing the day-to-day degradable network conditions for a range of link failure probabilities. Moreover, the proposed framework and methodology defines a way to combine all possible empirical dataset together for realistic link criticality evaluation.

To illustrate the proposed methodology, a case study is conducted using a portion of the Northern New Jersey network. Total system performance costs based on the assigned volumes of
each scenario are calculated using a GIS based post-processor that employs New Jersey specific cost functions (32–34). These costs are then used to detect and rank the critical links based on various criticality measures described in the paper. The results are found to validate the usefulness of the proposed framework, and demonstrate the potential bias if traditional localized and static measures are used. However, it should be noted that the proposed methodology and solution procedure is based on deterministic static traffic assignment, which assumes that drivers have perfect information about the network conditions. It can be more beneficial to investigate the impact of imperfect information by using stochastic user equilibrium assignment. Moreover, the proposed methodology can also be extended to the analysis of time-dependent traffic operations under day-to-day stochastic traffic conditions.

REFERENCES


