System Risk Curves: Probabilistic Performance Scenarios for Highway Networks Subject to Earthquake Damage

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Abstract: Monte Carlo simulation techniques are used with bridge fragility curves to evaluate bridge damage in terms of a bridge damage index, and highway network link damage in terms of a link damage index. Static, user-equilibrium analysis is used to evaluate total transportation network delay due to seismically induced damage inflicted on the Los Angeles and Orange County State highway and freeway network. A method of regional seismic risk analysis for highway systems is developed based on the definition of scenario earthquakes representing the seismic hazard of the region, and hazard-consistent probabilities are computed for each scenario. The final result of these efforts is a transportation system risk curve.


CE Database subject headings: Infrastructure; Earthquakes; Risk management; Transportation networks; Highways.

Introduction

Transportation systems include facilities such as highways, railroads, airports, and harbors. Services provided by the transportation system are critical to public welfare. If natural disasters such as earthquakes or floods strike, it is important to try and ensure that the transportation system remains operational. Past experience demonstrates that earthquake damage to highway components such as bridges, roadways, tunnels, and retaining walls can severely disrupt traffic flows. This lifetime damage negatively impacts the economy of the region (Brookshire et al. 1997; King et al. 1997; Werner et al. 1997), as well as post-earthquake emergency response and recovery. The extent of these impacts depends on the highway network’s level of functional impairment.

Bridges are the structural components of a transportation system that are probably most vulnerable to earthquakes. The seismic performance of bridges is difficult to model, because performance is a function of design, age, and local geotechnical conditions. In addition, earthquake intensity is also highly uncertain. We develop an analytical framework to integrate bridge performance models with transportation network models in the context of seismic risk assessment.

Literature Review

The literature reflects a growing interest on both sides of the Pacific in the seismic risks to spatially distributed systems. Iida et al. (1998) apply maximum origin-destination (O-D) flows to a road network after an earthquake to determine which traffic volumes should be regulated or controlled. Wakahayashi (1999) uses Birnbaum’s structure importance measure to identify critical links in the Kobe highway network. Terada and Aoyama (1997) define a redundancy model of road networks and evaluate an application of their model in the case of a disaster, but do not consider the correlation between seismic intensity and the vulnerability of links. Aya et al. (1997) simulate network damage from three earthquake events, but do not explain how they develop the link damage states that result. Chang and Nojima (2001) examine several alternative measures of physical performance of highway systems and analyze the correlation between these measures and observed traffic conditions following the Northridge and Kobe earthquakes. Their summary index of system performance degradation is a simplified measure that partially describes systems aspects of network performance. Kameda and Wakahayashi (1992) use network reliability analysis to explain traffic conditions following the Northridge and Kobe earthquakes. Their models are constructed overall performance measures. See Cho et al. (2001) for the details of such a comprehensive, single-scenario example.

Approach

This research develops methods for evaluating the performance of highway systems subjected to severe earthquake impacts, and
demonstrates the efficacy of these methods by applying them to the Los Angeles area highway network. This work extends the research by Chang et al. (2000) and research by Cho et al. (2001), who developed an integrated model of earthquake losses due to impacts on transportation and industrial capacity. The research extends Chang et al.’s approach by explicitly modeling transportation network performance and Cho et al.’s approach by introducing probabilistic earthquake scenarios.

Fig. 1 summarizes our approach. Fragility curves for individual bridges are developed on the basis of empirical damage data and dynamic analysis performed on bridge structures. These functions are used to generate network damage states for various scenario earthquakes by means of Monte Carlo simulation techniques. A representative yet computationally manageable set of 47 scenario earthquakes is selected to represent the regional seismic hazard associated with Los Angeles and Orange Counties, Calif. A larger set of scenarios is certainly feasible. Annual occurrence probabilities of these scenario earthquakes are calibrated based on current seismological data. Reductions in highway network performance are evaluated for each of these scenario earthquakes. A method for evaluating the seismic risk to the network is then developed by combining the seismic hazard represented by the scenario earthquakes and the resulting reductions in system performance. Changes in system performance are measured in terms of additional total network delay. These delays are calculated based on user-equilibrium network flow assignments.

A more complete approach that integrates transportation systems analysis and associated regional economic analysis is not yet computationally feasible for the large number of scenarios developed here. Adding to our approach a model capable of supporting a detailed regional economic analysis would greatly increase data requirements and computational burden (Cho et al. 2001).

The probabilistic scenarios are necessarily developed with attention to the spatial distribution of ground motion and infrastructure system damage within the urban area. This study focuses on the Los Angeles highway network system because:

1. The 1991 Southern California Association of Governments’ (SCAG) origin–destination survey data and network model are available;
2. The Los Angeles network system is large and complex, with many bridges and segments of elevated highways; and
3. This method of analysis can also be applied to the other highway networks and infrastructure systems.

Modeling Seismically Damaged Highway Networks

Estimating Bridge Damage States

Fragility Curves

A fragility curve describes the conditional probability that a bridge reaches at least a given damage state as a function of ground motion. Thus, any fragility curve is defined relative to a given damage state. Empirical fragility curves (Shinozuka 1998; Shinozuka et al. 2000) are developed on the basis of bridge damage records made after the 1994 Northridge earthquake. The peak ground acceleration (PGA) is used to characterize the intensity of the seismic ground motion, although use of other intensity measures such as peak ground velocity (PGV), spectral acceleration (SA), spectral intensity (SI), and modified Mercalli intensity (MMI) are reasonable. A fragility curve corresponding to each possible damage state is expressed in the form of a two-parameter lognormal distribution function. The two parameters (median and log-standard deviation) are estimated via a maximum likelihood method.

The likelihood function is

\[ L(c_1, c_2, c_3, c_4, \xi) = \prod_{k=0}^{N} \prod_{i=1}^{4} [P_{ik}]^{x_{ik}} = \prod_{k=0}^{N} \prod_{i=1}^{4} [P(a_i, E_k)]^{x_{ik}} \]

where \( a_i \) = PGA value to which bridge \( i \) is subjected; \( E_k \) = indicator variables for five discrete damage states: no damage \( (k=0) \), minor damage \( (k=1) \), moderate damage \( (k=2) \), major damage \( (k=3) \), collapse \( (k=4) \); \( x_{ik} = 1 \) or \( 0 \), depending on whether or not bridge \( i \) is subjected to \( a_i \) achieves damage state \( E_k \); \( P_{ik} = P(a_i, E_k) \) = probability that randomly selected bridge \( i \) will be in damage state \( E_k \) when subjected to PGA = \( a_i \); and \( N = \) total number of bridges inspected after the earthquake.

Under the logarithm assumption, the fragility function \( F(*) \) for the state of damage at least \( j \) has the analytical form

\[ F(a_i, c_j, \xi_j) = \Phi \left( \frac{\ln \left( \frac{a_i}{c_j} \right)}{\xi_j} \right) \]

where \( c_j \) = median of the fragility function associated with the damage state of at least \( j \); \( \xi_j \) = log-standard deviation of the fragility function associated with the damage state of at least \( j \); and \( \Phi(*) \) = standardized normal distribution function.

In the present study, all the bridges are assumed to have identical fragility characteristics and the set of 1,998 bridges inspected represents a sample of size 1,998 taken from this population of statistically identical bridges. This population is referred to as the composite population in this paper. This is the reason why we need only four fragility curves and hence need only four median values \( c_j \) (\( j=1,2,3, \) and \( 4 \)), and four corresponding log-standard deviation values \( \xi_j \) (\( j=1,2,3, \) and \( 4 \)). From the physics involved, however, these fragility curves are not supposed to cross each other, and an equal value of \( \xi \) is needed to satisfy this condition.
With a single value of $\zeta$ these fragility curves will appear as four parallel straight lines on a lognormal probability paper.

Three subsets of the composite population are then identified depending on the following three distinct attributes of the bridge: (1) number of spans (single versus multiple); (2) skew angle ($0^\circ$-20°, 20°-60°, >60°); and (3) soil conditions ($A$=hard, $B$=medium, and $C$=soft). These subsets are identifiable from the Caltrans’ (1994b) Northridge damage data. Shinozuka et al. (2003) estimated median values of $c_j$ ($j=1, 2, 3, 4$) and a log-standard deviation $\zeta$ for each sample taken from these second-level subpopulations, and estimated median values and a log-standard deviation for the third level subpopulations ($a$ and $b$, $b$ and $c$, and $c$ and $a$), and finally for the fourth-level subpopulations (18 combinations of $a$, $b$, and $c$). These 18 combinations arise because these are two attribute states in $a$, three attribute states in $b$, and three attribute states in $c$.

The five parameters $c_j$ and $\zeta$ in Eq. (2) are computed as $c_j^*$ and $\zeta^*$ by maximizing the log of the likelihood function, $\ln L(c_1, c_2, c_3, c_4, \xi)$, and hence $L$. The optimization requires solving the first-order conditions

$$\frac{\partial \ln L(c_1, c_2, c_3, c_4, \xi)}{\partial c_j} = \frac{\partial \ln L(c_1, c_2, c_3, c_4, \xi)}{\partial \xi} = 0, \quad \forall j$$

which is straightforward.

This procedure produces fragility curves classified by bridge damage states. From this definition of fragility curves, and the assumption that log-standard deviation is constant across all curves, it follows that

$$P_{i0} = P(a_i, E_0) = 1 - F(a_i, c_1, \xi)$$

$$P_{i1} = P(a_i, E_1) = P(a_i, c_1, \xi) - F(a_i, c_2, \xi)$$

$$P_{i2} = P(a_i, E_2) = F(a_i, c_2, \xi) - F(a_i, c_3, \xi)$$

$$P_{i3} = P(a_i, E_3) = F(a_i, c_3, \xi) - F(a_i, c_4, \xi)$$

$$P_{i4} = P(a_i, E_4) = F(a_i, c_4, \xi)$$

### Bridge Damage Index

Estimating fragility curves simultaneously on the basis of the PGA values and damage states reported by California Department of Transportation engineers for 1,998 bridges damaged by the Northridge earthquake produces a family of four nonintersecting curves, one for each of the damage states: (1) at least minor damage; (2) at least moderate damage; (3) at least major damage; and (4) collapse. Each fragility curve describes the cumulative probability of achieving or exceeding a given damage state as a function of PGA (see Fig. 2). The medians and log-standard deviations of these fragility curves are given in Table 1.

These fragility curves are used to generate Monte Carlo simulations of the damage states achieved by all Caltrans’ bridges in Los Angeles and Orange counties under a distribution of scenario earthquakes. Monte Carlo simulations produce a realization of a continuously distributed value between 0 and 1. These values and Eqs. (4)–(8) identify a single realization of the damage state a bridge might achieve given a ground acceleration of $a$. These bridge damage states are mapped to the bridge damage index (BDI) defined in Caltrans’ reports on bridge damage in the Northridge earthquake (Caltrans 1994a,b) (see Table 1).

### Identifying Link Damage States

The 1989 Loma Prieta earthquake that struck the San Francisco Bay area was a source of major disruption to the region’s transportation system, severing the Bay Bridge connection between San Francisco and Oakland. In contrast, the Los Angeles highway system showed more resiliency after the 1994 Northridge earthquake (JSCE 1994). This was accomplished by better coordinating use of undamaged secondary highways and arterials with the remaining capacity in the expressway network, which had suffered damage to a number of its bridges. The earthquake rendered Interstate-10 between Fairfax Avenue/Washington Boulevard and La Cienega/Venice Boulevard impassible due to the severe damage sustained by two bridges in this segment. This failure was temporarily addressed by defining an alternate route, thus restoring significant capacity. Other bottlenecks were handled similarly.

Ideally, each bridge should correspond to a separate link in the transportation network. In modeling practice, several bridges may exist in the same transportation link, and damage to any of these constituent bridges will to some degree impact the service provided by the link. The objective of converting bridge damage states to a BDI is to compute a link damage index (LDI) (Chang et al. 2000). The LDI quantifies link damage states. In this research, the LDI for each link is the square root of the sum of the squares of the BDI values assigned to all bridges associated with the link

$$LDI = \sqrt{\sum_{j=1}^{N} (BDI_j)^2}$$

where $N$=total number of bridges associated with the link; and $BDI_j$=bridge damage index for bridge $j$.

This definition of the LDI increases at a decreasing rate as the number of damaged bridges in a given link increases. If only a single bridge in a link is damaged, then the LDI value matches the BDI value. Competing specifications include setting the LDI value equal to the maximum in a set of BDI values. This

### Table 1. Bridge Damage States, Bridge Damage Index, and Fragility Curve Parameters

<table>
<thead>
<tr>
<th>Bridge damage state/fragility curve</th>
<th>Bridge damage index</th>
<th>Median PGA ($g$)</th>
<th>Log-standard deviation $\zeta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>No damage</td>
<td>0.00</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Minor damage, $j=1$</td>
<td>0.10</td>
<td>0.83</td>
<td>0.82</td>
</tr>
<tr>
<td>Moderate damage, $j=2$</td>
<td>0.30</td>
<td>1.07</td>
<td>0.82</td>
</tr>
<tr>
<td>Major damage, $j=3$</td>
<td>0.75</td>
<td>1.76</td>
<td>0.82</td>
</tr>
<tr>
<td>Collapse, $j=4$</td>
<td>1.00</td>
<td>3.96</td>
<td>0.82</td>
</tr>
</tbody>
</table>
competing specification would likely more closely track changes in traffic parameters, but the value taken on by Eq. (9) offers the advantage of increasing with repair requirements as more bridges are damaged.

In this case, the objective of computing LDI values is to translate these values into estimates of link traffic flow capacities and free flow speeds. The traffic capacity of a damaged bridge is a function of the remaining structural capacity of the bridge, the operating policies of local jurisdictions, and the context in which the damage occurs. If a single bridge is damaged, its residual traffic might be temporarily abandoned in the interests of safety. If a large earthquake damages many bridges in a single network, local authorities might choose it to protect the network-wide level of service by relying on the residual traffic capacities of damaged bridges.

In any event, alternate routes are assumed to provide reduced access to transportation services, both in terms of free flow speed and maximum capacity. We assume this is true even in redundant systems such as Los Angeles. A reasonable correspondence between link damage index values, link damage states, and representative changes in traffic capacities is summarized in Table 2. These figures are approximate, and refinements require further research.

### Table 2. Changes in Link Capacity and Free-Flow Speed as Function of Link Damage State

<table>
<thead>
<tr>
<th>Link damage state</th>
<th>&gt;LDI lower bound (%)</th>
<th>&lt;LDI upper bound (%)</th>
<th>Capacity (%)</th>
<th>Free flow speed (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No damage</td>
<td>0.00</td>
<td>0.50</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Minor damage</td>
<td>0.50</td>
<td>1.00</td>
<td>100</td>
<td>75</td>
</tr>
<tr>
<td>Moderate damage</td>
<td>1.00</td>
<td>1.50</td>
<td>75</td>
<td>50</td>
</tr>
<tr>
<td>Major damage</td>
<td>1.50</td>
<td>∞</td>
<td>50</td>
<td>50</td>
</tr>
</tbody>
</table>

The solution to the deterministic user-equilibrium assignment problem gives the link flows, $x_a$, that satisfy the user-equilibrium criterion when the matrix of origin–destination assignment, $q$, has been assigned to the network. This link-flow pattern can be obtained by solving the following mathematical program:

$$
\min z(x) = \sum_a \int_{0}^{x_a} t_a(\omega) d\omega
$$

subject to

$$
\sum_k f^{rs}_{k} = q_{rs}, \quad \forall r,s
$$

$$
x_a = \sum_r \sum_s \sum_k f^{rs}_{k} \delta^{rs}_{k}, \quad \forall a
$$

where $\omega$ = variable of integration; $t_a(x_a)$ = travel time on link $a$ when flow is $x_a$; $q_{rs}$ = required origin–destination flow between nodes $r$ and $s$; $\delta^{rs}_{k}$ = an indicator variable: 1 if link $a$ is on path $k$ between origin–destination pair $r-s$ and 0 otherwise; and $f^{rs}_{k}$ = flow on path $k$ connecting origin–destination pair $r-s$; $f^{rs}_{k} = (\ldots f^{rs}_{k}, \ldots)$.

The objective function is the sum of the integrals of the link performance functions. The value of this function does not have an intuitive economic or behavioral interpretation, but this objective function forces the solution to this convex programming problem to be a unique set of user-equilibrium path flows. Eq. (12) represents a set of flow conservation constraints. These constraints state that the combined flows across all paths connecting each O-D pair must be sufficient to accommodate the origin–destination flow requirement for the node pair. That is, all required trip rates must be assigned to the network. The non-negativity conditions in Eq. (14) are required to ensure that the solution of the program will be physically meaningful. The objective function, $z(x)$, is formulated in terms of link flows, whereas the flow conservation constraints are formulated in terms of path flows. The network structure enters this formulation through relationships coded in Eq. (13), which relate the path flow variables to the link-flow variables.

This static user-equilibrium flow formulation is simplistic, but it captures the most important economic aspect of competitive route choice: all used paths between a given origin–destination pair have the same, endogenously determined travel time. Unfortunately, this steady-state approach also suppresses the temporal variations in travel demand associated with any real road network, and oversimplifies travelers' objectives. Users do not merely seek to minimize delay. They also want to reduce variance in travel times, and to arrive at their destinations within a given time window. They have control over both their choice of route and their time of departure.

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The deficiencies inherent in the static model have been understood for some years (Hendrickson and Kocr 1981; Mahmassani and Herman 1984; Ben-Akiva 1985). Many scholars have invested considerable effort attacking the problem on both theoretical and computational fronts, in part because of the federal funding priority attached to research on intelligent transportation systems. There are several classes of competing macroscopic dynamic flow models, including formulations that rely on exit functions (Merchant and Nemhauser 1978; Carey 1992), time-space formulations (Zawack and Thompson 1987), and formulations relying on link travel delays (Friesz et al. 1993).

Accounting for these dynamic considerations substantially complicates the resulting model, regardless of how these aspects of the problem are represented. The problem presents a number of fundamental theoretical difficulties, including, depending on the formulation, nonunique solutions. Operational dynamic traffic assignment (DTA) programs are available and in use. These are usually based on mesoscopic traffic simulation approaches. Most major metropolitan planning organizations continue to exercise static formulations for transportation planning purposes, largely because of satisfaction with results and tractability concerns. This research incorporates a static version of the user-equilibrium flow model because the approach is robust and treating the static version of the problem reduces computational requirements. Despite the steady-state model’s theoretical limitations, analysis of Los Angeles traffic flows following the Northridge earthquake strongly suggest that, within a few days, traveler behaviors following an unexpected, significant loss of network capacity are surprisingly well predicted by a static formulation (Moore et al. 1997).

The previous formulation is a convenient way to characterize the user-equilibrium flow problem, but the problem is never stated in this form for a practical solution. Taken literally, Eqs. (13) require a complete enumeration of all network paths, and this is infeasible in any realistic network. User-equilibrium flows are conventionally obtained by solving a corresponding formulation that requires only link-flow variables

$$
\min z(x) = \sum_a \int_0^{t_a} t_s(\omega)d\omega
$$

subject to

$$
x_a = \sum_i x'_{as} \quad \forall a
$$

$$
\sum_a x'_{as} - \sum_a x'_{as} = q_{rs} \quad \forall r, s
$$

$$
x'_{as} \geq 0, \quad \forall a, s
$$

where $\omega =$variable of integration; $t_s(x_a) =$travel time on link $a$ when flow is $x_a$; $x'_{as} =$flow on link $a$ to destination $s$; $q_{rs} =$required origin-destination flow between nodes $r$ and $s$; $O_r =$set of all links outbound from node $r$; and $I_s =$set of all links inbound to node $r$.

The solution to this alternative problem produces a set of user-equilibrium link flows without identifying unique path flows. The problem is usually solved numerically to any desired degree of exactness by an application of the Frank–Wolfe algorithm (Leblanc et al. 1975).

Total network travel time can be expressed as

$$
\sum_a x_at_a(x_a)
$$

The analysis applies a summary index of total transportation cost (network delay), $\lambda$, based on the postearthquake network topology relative to pre-earthquake conditions. Network delay is

$$
\lambda = \sum_a x'_{as}(x_a) - \sum_a x_at_a(x_a)
$$

where $x_a =$equilibrium flow on link $a$ in the pre-earthquake (intact) network; $t_a =$equilibrium travel time on link $a$ in the pre-earthquake (intact) network; $x'_{as} =$equilibrium flow on link $a$ in the postearthquake (damaged) network; and $t'_{as} =$equilibrium travel time on link $a$ in the postearthquake (damaged) network.

**Risk Measures: Hazard-Consistent Probabilities**

In light of the uncertainties associated with future earthquakes, the methods for assessing earthquake loss estimation measures are necessarily probabilistic (Chang et al. 2000; Chang and Nojima 2001). At a given location, in a given year, expected earthquake losses $B$ can be expressed as

$$
B = \int_h L(\omega) \cdot p(\omega)d\omega
$$

where $\omega =$variable of integration; $h =$measure of ground shaking intensity at a given site, such as PGA; $L(h) =$loss function evaluated at ground motion intensity $h$; and $p(\omega) =$annual probability of an earthquake that produces a specified ground motion level.

The annual probability $p(h)$ for a given PGA level $h$ will differ at various sites across spatially distributed systems. Examples of spatially distributed systems include highway networks, water delivery systems, and electric power systems. In these cases, the spatial correlation between earthquake ground motions across many sites is important in determining system damage level as well as functionality.

In the case of highways, Eq. (21) can only be applied directly if the components of highway systems are treated as a collection of unrelated facilities, rather than as a distributed, functional system. However, this perspective is an unsatisfactory basis for system management decisions. A transportation agency may be interested in controlling postearthquake travel time delays, emergency response costs, or traffic disruption. These sorts of objectives require a systems analysis, and an approach that can account for the spatial correlation of earthquake ground motion and its impact on expected losses. Two modifications are made here to extend the standard framework for probabilistic seismic risk analysis to highway network systems. First, the probabilistic hazard is discretized to indicate individual scenario earthquakes. Second, loss must be estimated for the entire system, rather than at a particular site (Chang et al. 2000). In this framework, expected earthquake losses become

$$
B = \sum_{i=1}^N L(S_i|Q_i) \cdot p_i(Q_i)
$$

where $N =$total number of possible earthquakes; $L(\cdot) =$loss function; $S =$system performance; $Q_i =$ith possible earthquake; and $p_i(Q_i) =$annual probability of ith possible earthquake.

The number of possible earthquakes may be quite large, particularly in high seismicity areas. Consequently, evaluating
Eq. (22) for all possible earthquakes is generally infeasible. Instead, the methodology identifies a small set of representative earthquake events $Q_j$ ($j = 1, 2, \ldots, M$), where $M \ll N$, together with probabilities $p_j(Q)$ such that

$$\sum_{j=1}^{M} L(S(Q_j)) \cdot p_j(Q) = \sum_{i=1}^{N} L(S(Q_i)) \cdot p_i(Q_i) \quad (23)$$

The small set of events $Q_j$ is to be selected to represent different levels of system performance (or system damage state) $S$. Moreover, system loss $L(S)$ is a function of system performance level $S$. This contrasts with facility-specific losses $l(h)$, which are a function of site-specific ground motions $h$. In this case, system performance $S$ summarizes the network or system condition, while loss $L(S)$ is typically some monetizable measure of loss such as transportation network delay. The probabilities $p_j(Q_j)$ can be considered hazard-consistent probabilities in that, taken as a set, they fully represent the local hazard curve. However, these hazard-consistent probabilities are not the actual likelihoods for any of the individual events $Q_j$.

The events $Q_j$ are selected such that all of the major regional seismic source zones, as well as the range of damaging earthquake events that are credible for each zone, are represented in the set. For each scenario earthquake $Q_j$, regional ground motion, ensuing physical damage, and infrastructure system functionality are evaluated. Initially, probabilities are assigned to each event, and then iteratively revised until they are collectively consistent with regional probabilistic seismic hazard data. In this case, these probabilities permit construction of a system risk curve that denotes the annual probability of exceedance for various levels of postearthquake increases in network delay. This curve can be translated by the loss function $L(S)$ into a system loss curve analogous to a site-specific loss curve.

Table 3. Facility Characteristics

<table>
<thead>
<tr>
<th>Facility type</th>
<th>Traffic signals</th>
<th>Speed limit (mi/h)</th>
<th>Maximum capacity (FCU)$^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Limited access freeway</td>
<td>None</td>
<td>65</td>
<td>2,500</td>
</tr>
<tr>
<td>State highway</td>
<td>Present</td>
<td>35</td>
<td>1,500</td>
</tr>
</tbody>
</table>

$^2$PCU=passenger car units.

The resulting scenario earthquakes, together with their hazard-consistent probabilities, constitute probabilistic earthquake scenarios. This allows the highway network system’s earthquake-induced delays to be succinctly described in a system risk curve. These results pertain to the case without seismic hazard mitigation. A similar curve can be developed conditioned on mitigation measures if bridge fragility curves are revised to indicate the effects of seismic upgrading.

Application: Los Angeles State Highway System

Earthquakes have brought widespread destruction, not only to public infrastructure, but also to facilities for commercial, industrial, and cultural activities. After the Loma Prieta earthquake, damage to the Bay Bridge created considerable disruption, but commercial and cultural activities were less affected. Bay Area drivers did not give up traveling; and the associated reduction in the supply of transportation services resulted in heavy traffic congestion. The Kobe earthquake was more severe, disrupting social networks and activities. Driver origin–destination requirements with respect to the center of the region underwent substantial change.

In contrast, origin–destination requirements changed very little with respect to less damaged areas. The cost of travel, including congestion delay, does influence the demand for routes, destinations, and trips, but the most significant origin–destination impacts result from constraints on social and economic activities. Comprehensive treatment of postearthquake changes in travel demand requires an activity-based modeling approach. This involves intense data and computational demands (Cho et al. 2001). This approach is currently infeasible in a Monte Carlo context. Consequently, only pre-earthquake travel demands are applied in this study. This limitation will necessarily skew results associated with the most damaging earthquakes by overestimating travel demand and resulting congestion; but, at present, there is no analytical means available for shedding this distortion.

Network Model

Fig. 3 displays the freeway and state highway network for Los Angeles and Orange Counties, including 2,727 bridges. This relatively aggregate network representation consists of 118 nodes and 185 links. Nodes consist of locations where two or more highways intersect, as well as locations where a highway crosses the
Table 4. Time-of-Day Proportions by Trip Purpose

<table>
<thead>
<tr>
<th>Interval</th>
<th>Duration (h)</th>
<th>Home to work</th>
<th>Work to home</th>
<th>Other to work</th>
<th>Work to other</th>
<th>Home to nonwork</th>
<th>Nonwork to home</th>
<th>Other to other</th>
</tr>
</thead>
<tbody>
<tr>
<td>AM peak</td>
<td>6 a.m.–9 a.m. 3</td>
<td>0.3403</td>
<td>0.0152</td>
<td>0.1492</td>
<td>0.0166</td>
<td>0.1178</td>
<td>0.0158</td>
<td>0.1336</td>
</tr>
<tr>
<td>Midday</td>
<td>9 a.m.–3 p.m. 6</td>
<td>0.0786</td>
<td>0.0594</td>
<td>0.2199</td>
<td>0.2199</td>
<td>0.2665</td>
<td>0.1060</td>
<td>0.3725</td>
</tr>
<tr>
<td>PM peak</td>
<td>3 p.m.–7 p.m. 4</td>
<td>0.0196</td>
<td>0.3215</td>
<td>0.0343</td>
<td>0.3089</td>
<td>0.1643</td>
<td>0.1467</td>
<td>0.3119</td>
</tr>
<tr>
<td>Night</td>
<td>7 p.m.–6 a.m. 11</td>
<td>0.0944</td>
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<td>0.0256</td>
<td>0.0698</td>
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<td>24a</td>
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<td>0.4671</td>
<td>0.4290</td>
<td>0.5710</td>
<td>0.6184</td>
<td>0.3816</td>
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</table>

*The extent to which column sums differ from 0.5 reflects the degree to trip chaining by trip purpose.

boundary of the study area. There are two classes of links: (1) freeways; and (2) highways. The free flow speeds and capacities for each type are given in Table 3.

Southern California Association of Governments Origin–Destination Data

The O-D data used in this analysis consist of 1991 southern California origin–destination survey data (SCAG 1993) for 1,527 traffic analysis zones. Fig. 4 shows traffic analysis zones and zone centroids. These traffic analysis zones are different from census tracts. These O-D data describe a five-county area consisting of Los Angeles, Orange, Ventura, Riverside, and San Bernardino counties. The data consist of five O-D matrices classified by trip purpose: (1) home–work; (2) home–other; (3) other–other; (4) other–work; and (5) home–shop trips. Each matrix has 1,527 rows and columns. The home–work matrix contains data on both home-to-work and work-to-home trips. Similarly, the home–shop matrix contains both home-to-shop and shop-to-home trips.

These data include information about passenger trips throughout the day. Table 4 gives the proportion of trips across time of day and direction by trip purpose for four time periods. Table 5 further aggregates the a.m. peak and midday flows into representative 3-h proportions. These 3-h proportions and corresponding average vehicle occupancy data are the basis for origin–destination demands used to model network performance.

Aggregating Origin–Destination Requirements

The area under analysis consists of Los Angeles and Orange counties, and is thus smaller than the five-county SCAG planning region. Further, the transportation network used here provides a less detailed representation of geographic space than the 1991 southern California origin–destination survey data. The data from the 1991 SCAG origin–destination survey are aggregated to node O-D data for the study network via construction of Thiessen polygons. These polygons are defined relative to the locations of network nodes. The resulting O-D data consist of a 118 by 118 matrix. Fig. 5 shows this aggregate zone system. Figs. 6(a and b) summarize aggregate travel demand data for this system.

Representative Earthquake Scenarios

The scenario earthquakes were selected based on the results of studies by the California Department of Conservation, Division of Mines and Geology (Petersen et al. 1996), and by the Working Group on California Earthquake Probabilities (WGCEP 1995). The 47 scenario earthquakes selected for this analysis include most (13) of the maximum credible earthquake (MCE) events associated seismic source zones affecting Los Angeles and Orange counties, including events associated with the Elysian Park (blind thrust), Malibu Coast—Santa Monica—Hollywood, Newport—Inglewood, Palos Verdes, Raymond, San Andreas, San Jacinto, Santa Susana, San Fernando, Sierra Madre—Cucamonga, Simi—Santa Rosa—Northridge Hills, Verdugo, and Whittier—Elsinore faults; as well as 34 additional events consisting of smaller earthquakes of magnitudes 6.0, 6.5, and 7.0 with epicenters located at or near urban centers.

The annual occurrence probabilities for these scenario earthquakes were initially estimated based on seismological and empirical data, and then converted to hazard-consistent probabilities via calibration against a seismic hazard curve for the location of Los Angeles City Hall (WGCEP 1995), and a probabilistic hazard map describing a 10% probability of exceedance in 50 years (Petersen et al. 1996). See Chang et al. (2000). To initiate this calibration step, a sample of 47 sets of ground motion intensity parameters, PGA in this case, was generated for the 47 scenario earthquakes using the early postearthquake damage assessment tool (EPEDAT) (Eguchi et al. 1997), a loss estimation software package. EPEDAT allows the user to define a scenario earthquake by specifying its epicentral location, depth, and magnitude. EPEDAT then assigns the user-defined earthquake to the nearest seismic source zone capable of generating such an event. EPEDAT generates estimates of median PGA by census tract for the study region based on a ground motion attenuation model (Campbell 1997) and the USGS surficial database. Example results for Scenarios 1 and 2, a magnitude 7.1 MCE on the Elysian Park blind thrust fault, and a magnitude 7.3 MCE on the Malibu Coast fault, appear in Figs. 7 and 8, respectively.

Table 5. Three-h Proportions Based on Aggregate AM Peak and Midday Flows by Trip Purpose

<table>
<thead>
<tr>
<th>Home to work</th>
<th>Work to home</th>
<th>Other to work</th>
<th>Work to other</th>
<th>Home to shop</th>
<th>Shop to home</th>
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<th>Other to home</th>
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<tr>
<td>3 h ratioa</td>
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<td>1.70</td>
<td>1.72</td>
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<td></td>
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</tbody>
</table>

*[(AM peak+midday)/total]×(3 h/9 h).

bAVO=average vehicle occupancy.

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Given the PGA data for each scenario earthquake, the 2,727 bridges in Los Angeles County and Orange County are assigned their respective damage states via Monte Carlo simulation. The simulated damage state is expressed as the BDI, which is translated into the four categories of: (1) minor damage; (2) moderate damage; (3) major damage; and (4) collapse. The link damage is expressed as the LDI, which is computed for each link based on the BDI values for all bridges in the link. The LDI value is translated into link traffic capacity. Ten Monte Carlo simulations of bridge damage are executed for each of the 47 scenario earthquakes. User-equilibrium flows are computed for each. Bridge damage and network performance results are averaged across the ten simulations.

**System Risk Curve for Los Angeles Highway Network**

The average incremental network delay for each scenario earthquake is given in the Appendix. The estimated total travel time for the 3 h of demand imposed on the pre-earthquake network is $8.90 \times 10^4$ h. This is a baseline value. These 47 events, taken together with their hazard-consistent probabilities, allow the Los Angeles and Orange County highway system’s risk of earthquake-induced network costs to be succinctly described in a system risk curve, as shown in Fig. 9. This curve plots the annual probability of exceedance, i.e., the cumulative, hazard-consistent probability,
for different levels of network delay. Each coordinate in the figure represents one of the scenario events. Fig. 9 also references the 1994 Northridge earthquake, in which bridges collapsed on 1-10 (Santa Monica Freeway), on I-5 (Golden State Freeway), at the I-5/S-14 (Antelope Valley) intersection, and on SR-118 (San Fernando Valley). According to the risk curve shown in Fig. 9, the annual probability of exceeding this impact on system performance is 0.018. This would make the probability of exceeding Northridge-level disruption in a 50 year interval about 0.60.

Modeling the increase in network delay resulting from the Northridge event produces an estimate $\lambda = 0.42 \times 10^5$ h for 3 h of demand, or 0.86 min/passenger car unit (PCU). This average is consistent with experiences following the Northridge earthquake, but suppresses the considerable variance in travel times that travelers experienced. The Los Angeles transportation network is highly redundant. Further, Caltrans and the Los Angeles Department of Transportation (LADOT) cooperated closely to better manage traffic flows following the Northridge earthquake (Leung and Yee 1999; Okazaki 1999). As a result, most travelers experienced no incremental delay as a result of the earthquake. Some travelers, a relatively small minority, experienced high delays.

**Conclusions and Extensions**

This research combines earthquake and transportation engineering techniques to better characterize the system risk curve for...
the Los Angeles and Orange County, Calif. highway system. The work offers insight into similar efforts relating to any life-line system: Knowledge of seismic hazard must be combined with the means to adequately model system performance. In the case of a transportation network, this means, at a minimum, solving a large-scale nonlinear programming problem. Flows in power and water networks follow different rules than flows in transportation networks. System performance must be characterized accordingly in these cases, but the basic approach described here applies to these other spatially distributed systems as well.

**Transportation Supply versus Transportation Demand**

This work has some important limitations. Transportation is a derived demand, even more so than is true of other infrastructure-based services. Transportation is not an end in itself; and the demand for transportation services is implicitly a demand for whatever goods, services, and opportunities travel makes possible. The postearthquake level of service available from the transportation network is an economic equilibrium defined by the interaction between supply and demand. Damage to the network suppresses supply and reduces level of service. Damage to buildings interrupts the activities these structures support, including provision of shelter to households, and thus suppresses the demand for transportation that would otherwise be associated with these activities. Reliably predicting postearthquake level of transportation service requires simultaneous treatment of these demand and supply impacts. The origin-destination data used here does not capture the 47 earthquake scenarios' respective impacts on transportation demand. Using pre-earthquake O-D data is reasonable and effective for low magnitude earthquakes with relatively low impacts on economic and social activities, but this compromise certainly overestimates the network delay costs associated with the most serious earthquakes.

Previous work (Cho et al. 2001) specified a tractable computational model that accounts for the effects of earthquakes on transportation networks, building stocks, and regional economic activities. This previous model better accounts for transportation demand after an earthquake because it treats interactions between the urban economy and transportation infrastructure. However, this approach, while convergent, is computationally too burdensome to be combined with the approach presented here. Better models are needed to describe the postearthquake demand for all infrastructure services, including transportation services. It may well be possible to identify more tractable approaches to modeling demand than are currently available.

**Retrofit, Reconstruction, and Network Design**

The expected benefits of mitigation consist of expected costs foregone because mitigation was undertaken. Comparing the results of mitigation alternatives (including no mitigation) is the logical basis for benefit–cost analysis of proposed mitigation measures (Chang et al. 2000; Cho et al. 2001). An optimal mitigation plan requires benefit estimates that are full, comprehensive, and systemwide. This is a difficult problem at the level of large metropolitan areas, because urban risk mitigation alternatives define a combinatorially large set of options. Resources for retrofit and other mitigation measures are scarce, and the benefits of these measures must be traded off against the costs of other public expenditures. Creation of a postmitigation risk curve such as Fig. 9 provides the basis for a standard, decision analytic framework for evaluating mitigation options. However, even with the means to make a systematic comparison of mitigation measures, identification of an optimal (or even good) mitigation strategy remains challenging. The range of site-specific mitigation options in a spatially distributed system is certainly too large to permit an explicit enumeration and comparison of alternatives, even if mitigation budgets are small.

One way to approach this challenge in the transportation context is to treat mitigation, retrofit, and reconstruction decisions as large-scale transportation network design problems. In the most general terms, the network design problem is an optimization problem in which network authorities must determine the set of discrete facility investments that maximizes improvements in system performance. Resources are constrained, so these decisions must be made relative to a budget constraint. The deterministic version of the problem is further complicated by the fact that users compete for network access. The flows that occur on a transportation network are not the flows that minimize network delay. Instead, the flows that occur will satisfy user-equilibrium conditions. The goal of network design is to find the facility investments that offer the greatest improvement in system performance given that users compete. Conventional approaches to the deterministic version of these problems combine mathematical programming with bilevel control or implicit enumeration techniques. Mitigation investments such as retrofit decisions inject stochasticity into an already difficult class of deterministic problems. It is unclear how these techniques will best be applied to metropolitan area models, although access to system risk curves will be a necessary step in structuring decisions that account for the stochastic aspects of the problem.

The analytical challenge would be worst following an earthquake, in which case: (1) the problem would be deterministic; (2) budgets would be larger; and (3) the network design problem would consist of alternative reconstruction sequences rather than mitigation measures. The benefits of any feasible reconstruction sequence must be computed from the corresponding sequence of improvements in system performance. Net benefits are determined by comparing this sequence of improvements to the cost of reconstruction. This problem cannot yet be treated tractably, but the Kobe recovery from the Great Hanshin earthquake provides insights into how to reduce the size of this feasible set.

**Acknowledgments**

This work has contributed to ongoing investigations supported by National Science Foundation Award No. CMS-9812503 (ISMHR), by the NSF Earthquake Engineering Research Centers Program under Award No. EEC-9701568, and by the Institute for Civil Infrastructure Systems (ICIS), sponsored by the NSF under Award No. CMS-9728805. Use of EPEDAT was provided courtesy of EQE International, now ABS Consulting. The writers are grateful for this support. This work has been substantially improved by the contributions of three anonymous referees. All opinions, findings, conclusions, and recommendations expressed in this document are those of the writers, and do not necessarily reflect the views of the National Science Foundation.
### Appendix. Los Angeles Scenario Earthquakes

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Fault</th>
<th>Type*</th>
<th>Magnitude</th>
<th>Annual probability</th>
<th>Probability of exceedance</th>
<th>Network delay $10^2$ h</th>
</tr>
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