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Network Capacity Reliability Analysis Considering Traffic Regulation after a Major Disaster

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Abstract The focuses of this paper are optimal traffic regulation after a major disaster and evaluation of capacity reliability of a network. The paper firstly discusses the context of traffic regulation and its importance after a major disaster. Then, this problem is formulated as an optimisation program in which the traffic regulator attempts to regulate the amount of traffic movements or access to some areas so as to maximise the traffic volumes in the network while (a) link flows must be less than link capacities and (b) re-routing effect due to changes of traffic condition in the network is allowed. The re-routing behaviour is assumed to follow Probit Stochastic User's Equilibrium (SUE). The paper explains an optimisation algorithm based on an implicit programming approach for solving this problem with the SUE condition. With this optimisation problem, the randomness of the link capacities (to represent random effects of the disaster) is introduced and the paper describes an approach to approximate the capacity reliability of the network using Monte-Carlo simulation. The paper then adopts this approach to evaluate the performances of different traffic regulation policies with a small network and a test network of Kobe city in Japan.

Keywords Network capacity reliability · Traffic regulation · MPEC and Probit Stochastic User Equilibrium

1 Introduction

In an urban area, urban activities carried out under a normal circumstance rely largely on transportation systems especially road networks. However, the road network and transportation system in general are not totally disaster-proof. In the

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Great Hanshin-Awaji Earthquake occurred in 1995 in Japan, the road network system was seriously deteriorated and was in fact the infrastructure which was mostly damaged. Similarly, in the Chi-Chi Earthquake occurred in 1999 in Taiwan most of the roads and bridges were hampered by the earthquake forcing the emergency activities to be mainly carried out by helicopter or walking (Chi-Chi Reconnaissance Team, 2000). In the recent Indian Ocean Tsunami disaster, the road network in Indonesia in the vicinity of the tsunami wave was disrupted by around 31% (Athukorala and Resosudarmo, 2005).

Generally, the capacity of the deteriorated road network was recovered only partially by some temporary measures. It is evitable to take a rather longer period until the full capacity of the road network system can be restored given the level of damage. However, after the initial period of the disaster various aid activities, emergency or rescue activities, or other normal activities will take place. Kurauchi and Iida (1998) analysed that changes in the automobile trip pattern within the Hanshin region road network and discovered a substantial increase in the automobile trips with a short-distance as compared to the figure in the normal condition. The increase was mainly related to recovering activities such as purchasing goods and material.

The road network was found to be more robust to the disaster damage as compared to the other modes (e.g., rail) and after the disaster all travellers will have to inevitably shift to the road network to access the life supplies (IATSS, Research Report (2000)). Under this circumstance, the management of the road network is critically important particularly after the major disaster to cope with the degraded level of capacity and increase in travel demand in order to ensure the level of service for certain activities.

In the context of network reliability, several researches have been carried out to address several concerns over the reliability of the transportation network. In particular, in the field of network analysis against disasters the main aim has been to evaluate the robustness/vulnerability of the network or identify critical components of the network. For instance, Du and Nicholson (1997) evaluated the connectivity reliability of degradable transport networks in which the connectivity reliability is inferred to the probability of all OD pairs to still be connected after different possible road closure patterns. Bell (1999) proposed a game theoretic based approach between the "evil entity'' aiming to degrade the network so as to maximise the total travel time and the travellers re-routing to minimise their travel time. The result of this game will be the most critical link in the network. D'Este and Taylor (2003) defined the concept of node vulnerability whose accessibility index decreases significantly with a small number of links degraded.

Despite the growing interests in the area of network reliability, there have been a rather small number of researches which evaluate the potential performance of different traffic management strategies or policies under the disruption. This is indeed the main focus of this paper where we aim to develop an evaluation scheme of the performance of different traffic management strategies under the randomly degraded network condition.

In practice, after a major disaster the assigned network manager (e.g., police) will be able to implement a form of traffic regulation to control the traffic movement in the network. For instance, an area access regulation may be put in place to control the level of traffic entering some particular areas so as to maintain the level of service in those areas under the degraded network capacity. The legal power or specific strategy for the traffic regulation will depend largely on the prior analysis and evaluation. One of the main indicators which may be adopted to compare the performances of different regulation strategies (e.g., area access control as contrast to link access control) is the index of capacity reliability.

The concept of the network capacity reliability was first proposed by Chen et al. (2002).The network capacity is defined as a uniform multiplier of all OD demands which generates the equilibrium link flows satisfying link capacities. The introduction of link capacity in the analysis is to ensure a certain level of service on all links in the network (e.g., non-congested condition). In this paper, the OD demand multipliers are allowed to be different by OD movements representing traffic demand regulation parameters. The capacity reliability for a certain traffic regulation strategy can then be defined as the probability of that regulation strategy to generate the allowed traffic volume in the network more than a specified criteria under the random link capacities.

For a given traffic regulation strategy and a realised state of the degraded link capacities, the actual traffic demand control parameters (i.e., the value of the OD demand multiplier) can be optimised so as to maximise the total traffic volume in the network considering the re-routing behaviour without violating the link capacity constraints. In this paper, travellers' route choices are assumed to follow the concept of Probit stochastic user equilibrium (SUE). This problem can be categorised as an instance of a Network Design Problem (NDP).

The paper adopts the implicit optimisation approach proposed in Connors et al. (2006a) to solve this problem. This problem is then integrated as a part of the overall evaluation framework in which the Monte-Carlo simulation is employed to randomly generate different states of link capacities (under given probabilities defined as priori) as an input to the sub-problem. The detail of this overall evaluation algorithm will be discussed in Section 3.

This paper is structured in to further four sections. The next section presents the mathematical formulation of the capacity reliability evaluation problem. The third section explains the solution algorithm for the sub-problem in the evaluation process. The algorithm will then be used to test the performances of different possible traffic regulation strategies with a small network for demonstration purpose and with a network of Kobe city. The last section finally concludes the paper.

2 Mathematical Formulation of Traffic Regulation Problem and Capacity Reliability Evaluation

2.1 Probit Based Route Choice Equilibrium Model with Capacity Constraint

Let $G(A, N)$ denotes a directed graph comprising of a set of directed arcs, A, and nodes, N. Let $\mathbf{x}$ denoted a vector of link flows with the size of $|A|$. Define $\mathbf{q}$ with the size of $|R|$ (R is the set of OD pairs) as a vector of travel demand in which each entry, q_{rs}, is associated with a demand for an OD movement from nodes r to s ($r \neq s$; $r, s \in N$). For each OD pair, rs, flows can move from r to s through different paths (p) in the network. Let $\mathbf{f}$ denote the vector of path flows with size equal to the number of path ($|H|$, where H is the set of paths) in which each element, f_p, denotes amount of path flow on path p where $p \in \Pi_{rs}$, and Π_{rs} denotes the set of paths between an OD pair rs. The matrix Ω denotes the path-OD incidence matrix (with the size of $|H| \times |R|$) in which $\Omega_{p,r} = 1$ if path p is associated with OD pair r and 0 otherwise.

The relationship between a path and links (i.e., path is a combination of a number of links in the network) is defined through a path-link incident matrix, denoted by Δ (with the size of $|A| \times |H|$) in which its element, $\Delta_{a,p} = 1$ if link a is related to path p and 0 otherwise.

Next, the Probit based Users' Equilibrium (SUE) condition for travellers' route choices is introduced. Define $t_a(\mathbf{x})$ and $c_p(\mathbf{f})$ as a link and path cost for link a and path p, respectively. In this paper, we assume that $t_a(\mathbf{x})$ is a continuous twice differentiable function and monotone with respect the $\mathbf{x}$, and $t_a(\mathbf{x})$ is defined following a standard separable BPR function: $t_a(\mathbf{x}) = \alpha_a + \beta \cdot (x_a/s_a)^{\lambda_a}$. Define $\mathbf{c} = \Delta\mathbf{t}$ for the relationship between path and link costs and the perceived dis-utility of travelling on path p is:

$$U_p = c_p(\mathbf{f}) + \varepsilon_p \tag{1}$$

where the stochastic term, ε_p, is assumed to be a joint non-degenerate multivariate normal distribution (a way to define this term will be discussed later in the numerical example). We assume that the variance–covariance matrix of ε to be a non-singular matrix. The travellers between OD pair rs will choose to travel on the path with the minimum perceived dis-utility. The corresponding choice probability of path p can then be defined as:

$$P_p(\mathbf{U}) = \Pr\left(U_p \leq U_{\tilde{p}} \forall \tilde{p} \in \Pi_{rs}\right) \tag{2}$$

Thus, we can define the fixed point condition for the Probit SUE as:

$$\mathbf{x} = \Delta \cdot \left\{(\Omega \cdot \mathbf{q}) \otimes \mathbf{P}\left(\Delta^T \cdot \mathbf{t}(\mathbf{x})\right)\right\} \tag{3}$$

where $\otimes$ and $\div$ denotes the element-wise multiplication and division operators for matrices in which $\mathbf{A} \otimes \mathbf{B} = \mathbf{C}$ ($\mathbf{A}$, $\mathbf{B}$, and $\mathbf{C}$ have the same size) and $c_{i,j} = a_{i,j} \cdot b_{i,j}$ (i and j denotes row and column of the matrices, respectively). Following the Brower's fixed point condition, it is trivial to prove that for a given vector of $\mathbf{q}$ there exists a solution vector $\mathbf{x}$ which satisfies Eq. (3). Denote $\mathbf{x}^*$ as vector of SUE link flows satisfying the fixed-point condition in Eq. (3).

2.2 Traffic Regulation Problem Formulation as MPEC

In this section we will formulate this problem as a Mathematical Program with Equilibrium Constraints (MPEC). Let θ denote a vector with the size of $|R|$ in which each entry, $0 \leq \theta_{rs} \leq 1$, represents the ratio of traffic allowed to travel between the OD pair rs. For a given normal travel demand between OD pair rs, denoted q_{rs}, the allowed amount of traffic to travel after a major disaster will be $\theta_{rs}q_{rs}$. Thus, the total amount of traffic in the network can be defined as $\theta^T \cdot \mathbf{q}$. In the traffic regulation problem, the regulator attempts to set θ so as to maximise the total traffic volumes in the network whilst keeping the link flows lower than the link capacities,

s_j, to avoid any congestion. This can be defined mathematically as (referred to as the REG-problem):

$$\begin{aligned} &\underset{(\mathbf{x},\theta)}{\text{Max}}\, Z \equiv \theta^T \cdot \mathbf{q} \\ &s.t. \\ &\mathbf{x}^*(\theta) \leq \mathbf{s} \\ &\mathbf{0} \leq \theta \leq 1 \end{aligned} \tag{4}$$

where following the description in the previous section $\mathbf{x}^*(\theta)$ is defined as the SUE link flow vector for a given vector of demand (controlled by θ) satisfying the fixed-point condition of:

$$\mathbf{x}^* = \Delta \cdot \left\{ (\Omega \cdot \mathbf{q} \otimes \theta) \otimes \mathbf{P}\left(\Delta^T \cdot \mathbf{t}(\mathbf{x}^*)\right) \right\} \tag{5}$$

For a given vector of θ, the existence of $\mathbf{x}^*(\theta)$, again, follows the Brower fixed-point theorem. Note that the SUE link-flow in Eq. (4) is written as an implicit function of θ to signify that as the allowed travel demand in the network change the SUE link flows may also change accordingly. The constraint of $\mathbf{x}^*(\theta) \leq \mathbf{s}$, where $\mathbf{s}$ is a vector of link capacity, ensures that the resulting SUE flows do not violate the link capacities.

The objective function from the solution of Eq. (4) can be considered as the capacity of the degraded network. This can be used to evaluate the capacity reliability of the network as defined in the next section. The existence of a solution of Eq. (4) can be shown that for a given value of $\theta \otimes \mathbf{q}$, one can reduce the level of demand in the network until all SUE link flows satisfy the link capacities. The trivial case for this is that of $\theta = \mathbf{0}$. Thus, the REG-problem definitely has at least one solution satisfying the optimality condition.

2.3 Definition of Capacity Reliability

Given a directed graph $G(A, N)$, each link $a \in A$ may be degraded by the effect of the disaster. We assume that the nodes in the network will not be degraded in this analysis for simplicity. Once a link is degraded, its capacity may be reduced (which may be due to a closure of lanes, road disruption, etc.). We assume that each link has an independent probability of failure ($0 \leq \gamma_a \leq 1$) and uniform probability of the level of degradation. With a realised state of the link capacities in the network (after the disaster), the traffic regulation scheme as described by Eq. (4) is assumed to be in place. The probability of each state of the network is denoted by η_k.

From Eq. (4), we can obtain the maximum level of travel demands in the network which are allowed to travel, denoted O_k. Let O^* denotes the traffic volume as defined by Eq. (4) with a non-degraded network. We can then define the ratio between the traffic volumes after and before the degradation of the network (under state k) as $\mu_k = O_k/O^*$. Indeed, Chen et al. (2002) adopted this measure to define the capacity reliability as:

$$R(\overline{\mu}) \equiv \Pr(\mu_k \geq \overline{\mu}) = \sum_{\forall k} (\eta_k \cdot \alpha_k) \tag{6}$$

where $\overline{\mu}$ is defined as an acceptable level of capacity of the network (defined by the regulator) and $\alpha_k = 1$ if $\mu_k - \overline{\mu} \geq 0$ and 0 otherwise.

Evaluating Eq. (6) exactly for all possible network states may be too computationally intensive and even impossible for the case with continuous capacity. For instance, for a network with 50 links (and assume three discrete levels of link capacity after degradation), there will be around 3^{50} states. If we assume a continuous level of degraded capacity, the number of possible states becomes infinite. Thus, we adopt the method of Monte-Carlo simulation to estimate the capacity reliability measure. The procedure is as follows:

Step 0: Set sample number $k = 1$;
Step 1: Generate a uniform random number Y_a ranging from 0 to 1 for each link;
Step 2: if $Y_a < \gamma_a$ (link failure probability), generate another uniform random number B_a, and reduce the capacity of link a as $(1 - C_a B_a)\, s_a$, where C_a is an input parameter.
Step 3: Solve the REG problem to obtain O_k, maximum traffic volume accepted on the degraded network of k.
Step 4: If $k < k_{\max}$, $k = k + 1$ and go to Step 1. Otherwise terminate.

From O_k, capacity network measures considering traffic regulation with threshold of $\overline{\mu}$ can be calculated as follows.

$$R(\mu_r) = \Pr(\mu \geq \mu_r) = \sum_{k=1}^{k_{\max}} \upsilon_{k,\overline{\mu}} \Big/ k_{\max}$$

where $\upsilon_{k,\overline{\mu}} = 1$ if $O_k/O^* \geq \overline{\mu}$, and 0 otherwise.

3 Implicit Optimisation Algorithm for Optimal Traffic Regulation Problem

The REG problem as defined in Eq. (4) can be solved by many available optimisation routines provided that the derivatives of all functions involved can be calculated. In this case, we adopt the sequential quadratic programming (SQP) algorithm from the ‘fmincon’ solver in MATLAB® (see Bazaraa et al., 1993 for the detail of SQP). Noteworthy that due to the non-convexity of the SUE link-flows as a function of θ, there could be multiple optimal solutions for the REG problem. Under this condition, we can only guarantee the local optimum from the optimisation algorithm.

The objective function and the bound constraints of θ in Eq. (4) are relatively simple in which their values and related derivatives can be analytically defined. For the non-linear inequality constraints of the SUE link-flows and the link capacities, the evaluation of these constraints involves solving the Probit SUE assignment for a given vector of θ. In this paper, the algorithm for finding SUE link flows for a given vector of θ employs the method of successive average as defined in Sheffi (1985) and the method of (Mendell and Elston, 1974) is adopted for evaluating the Probit path choice probability. Note that other alternative methods can also be adopted to carry out this task (see Rosa, 2003 for further discussions).

The derivative of $\mathbf{x}^*(\theta)$ with respect to θ can be defined through the sensitivity analysis of the SUE link flows with the perturbation of θ (Clark and Watling, 2002). Briefly, a gap function of Eq. (5) can be defined as:

$$\mathbf{g}(\theta) = \mathbf{x}^* - \Delta \cdot \left\{ (\Omega \cdot \mathbf{q} \otimes \theta) \otimes \mathbf{P}\left(\Delta^T \cdot \mathbf{t}(\mathbf{x}^*)\right) \right\} \tag{7}$$

Applying the Taylor first order approximation to $\mathbf{g}(\theta)$ around θ_0 and $\mathbf{x}^*(\theta_0)$ yields:

$$\mathbf{g}(\theta) \approx \mathbf{g}(\theta_0) + \nabla_{\mathbf{x}}\mathbf{g}(\theta_0) \cdot (\mathbf{x}^*(\theta) - \mathbf{x}^*(\theta_0)) + \nabla_{\theta}\mathbf{g}(\theta_0) \cdot (\theta - \theta_0) \tag{8}$$

where $\nabla_{\mathbf{x}}\mathbf{g}(\theta_0)$ and $\nabla_{\theta}\mathbf{g}(\theta_0)$ are the jacobians (evaluated at θ_0) of the gap function vector with respect to $\mathbf{x}$ and θ, respectively, which are:

$$\begin{aligned} \nabla_{\mathbf{x}}\mathbf{g}(\theta_0) &= \mathbf{I} - \Delta \cdot \left[(\Omega \cdot \mathbf{q} \otimes \theta) \cdot 1_{(1,|H|)} \otimes \mathbf{I} \right] \cdot \nabla_{C}\mathbf{P} \cdot \Delta^T \cdot \nabla_{\mathbf{x}}\mathbf{t} \\ \nabla_{\theta}\mathbf{g}(\theta_0) &= -\Delta \cdot (\mathbf{P} \otimes (\Omega \cdot \nabla_{\theta}\mathbf{q})) \end{aligned} \tag{9}$$

From Eq. (8) since the values of the gap function at θ and θ_0 must be both zero, one obtains:

$$\frac{\mathbf{x}^*(\theta) - \mathbf{x}^*(\theta_0)}{\theta - \theta_0} \approx -(\nabla_{\mathbf{x}}\mathbf{g}(\theta_0))^{-1} \cdot \nabla_{\theta}\mathbf{g}(\theta_0) \tag{10}$$

Then, the gradient of the SUE link flows with respect to θ can be derived as:

$$\nabla_{\theta}\mathbf{x}^*(\theta) = \lim_{\theta \to \theta_0} \frac{\mathbf{x}^*(\theta) - \mathbf{x}^*(\theta_0)}{\theta - \theta_0} = -(\nabla_{\mathbf{x}}\mathbf{g}(\theta_0))^{-1} \cdot \nabla_{\theta}\mathbf{g}(\theta_0) \tag{11}$$

see Sumalee et al. (2006) and Connors et al. (2006b) for the discussion on the numerical calculation and existence of Eq. (11).

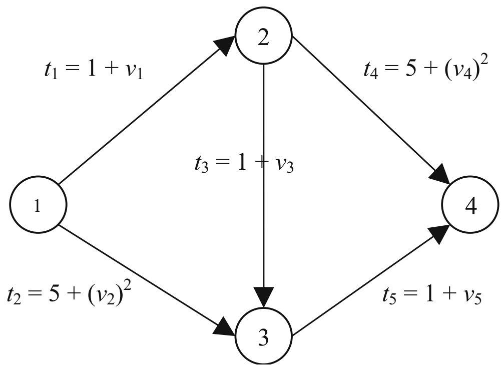
4 Numerical and Policy Tests

4.1 Test with a Five-link Network

This section illustrates the application of the methodology proposed in Sections 2 and 3 to a toy network example. The five link network with two OD pairs as shown in Fig. 1 is adopted for the test. The variance–covariance matrix of perceived path costs is derived from the pre-defined values of the variances of perceived link travel costs using the link-path incidence matrix. For instance, path 1 in the five-link network is defined as the path from links 1 to 4 and path 3 in the network is defined as the path from links 1 to 3 and 5. If the link variances of all links are defined as 1, then the covariance between paths 1 and 3 is 1 (due to the variance on link 3 which is the overlapping link of both paths).

In this test, the link cost variances for all links are defined as 1. Two OD pairs are defined, from nodes 1 to 4 and from nodes 1 to 3. The total demands in the base case for these two OD pairs are assumed to be 10. The initial test is conducted to investigate the performance of the implicit programming in solving the problem. With the normal probit SUE condition, the equilibrium link flows are 15.2129,

Fig. 1 Test network



4.7871, 9.8929, 5.32, and 4.68 for links 1 to 5 in that order. In the initial test, the capacity of all links is set to be 10. The implicit programming algorithm is then applied to solve the REG and gave θ_1 = 1.00 and θ_2 = 0.3912 as the optimal solution with the total demand in the network of 13.9121. The resulting SUE flows are 10, 3.9121, 7.5747, 2.4253, and 1.4869 for links 1 to 5, respectively, which all satisfy the link capacities of 10.

To verify this result, Fig. 2 depicts the comparison between, on the vertical axis, the aggregated level of link capacity violation (if greater than 0 there is at least a link with the flow higher than the link capacity) and, on the horizontal axis, the total trips in the network. This figure was generated by finding the SUE link flows for each of the given values of θ_1 and θ_2. The highest level of the value of the horizontal axis with the corresponding level on the vertical axis of zero (all link

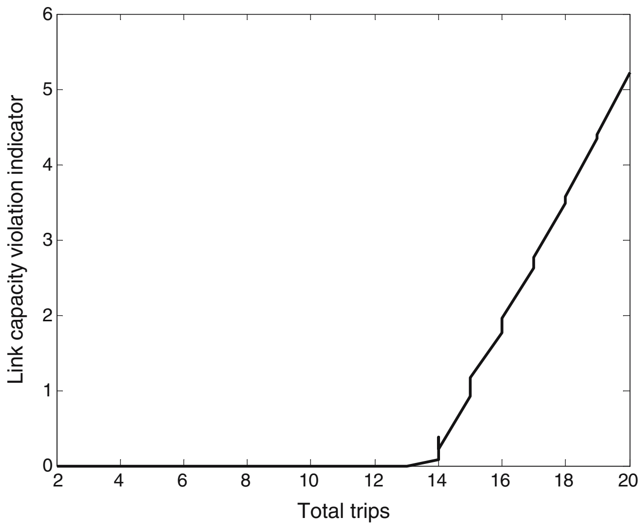


Fig. 2 Total number of trips loaded into the test network and the associated link capacity violation indicators

flows satisfies the link capacities) is between 13 and 14 which is consistent with the result from the implicit programming (13.9121).

After this initial test, two cases of traffic regulation are defined for testing their performances in terms of the network capacity reliability. The first is with two parameters of OD demand control, θ_1 and θ_2, one for each OD pair controlling the level of OD demand allowed to travel in the network. The second case is with only one parameter of OD demand control applied to both OD pair, θ_1.

For the first test, the range γ_a values (link failure probabilities) is tested (from 0.1 to 1) as well as the acceptable level of network capacity, $\overline{\mu}$ (ranging from 0.1 to 0.95). Figure 3 shows the plot of the result.

This result is based on the value of C_a of 0.6 for all links (see Section 2.3) and the number of iteration of the MC adopted is 50. As expected, the higher the link failure probability the lower the capacity reliability. Similarly, the higher the acceptable capacity level, the lower the capacity reliability indices.

Similar assumptions are made for the second test but with only one demand control parameter applied to both OD pairs. Figure 4 below plots the difference between the capacity reliability indices as found from the first and second tests (cases 1–2). As expected, most of the cases have positive values implying the higher capacity reliability indices in the case with two control parameters. This is due to a higher degree of freedom for the REG. However, there exist some negative values which may be mainly due to either the sampling error from the MC simulation (only 50 samples are used) or the local optimum of the values of θ_1 and θ_2 found by the implicit programming algorithm.

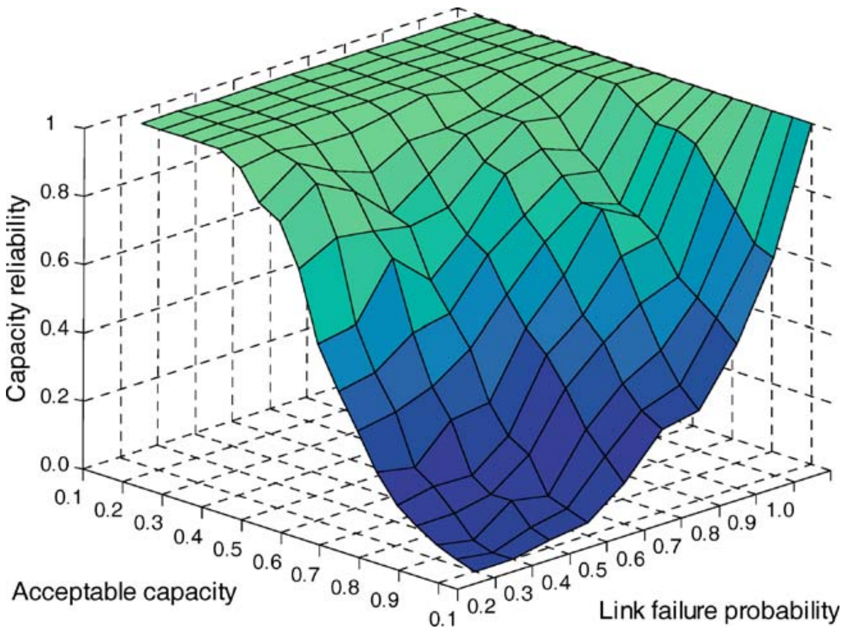


Fig. 3 Capacity reliability test with the small test network with different values of link failure probability and acceptable levels of demand

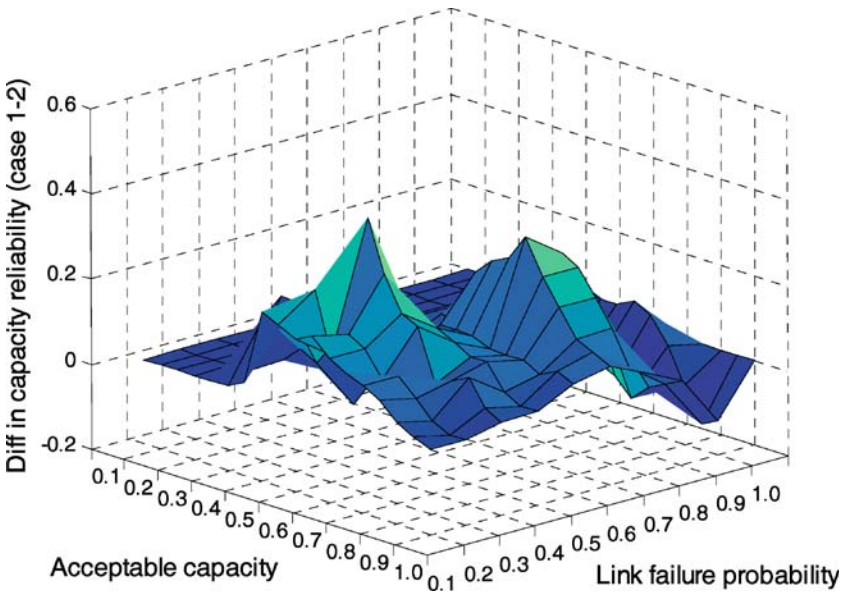


Fig. 4 Comparison between the capacity reliability indices for the test with the small network with two and one OD demand control parameters

Comparing between the two cases, the highest value of the difference between the capacity reliabilities is 0.40 which significantly suggests the higher performance of the first regulation scheme. As mentioned, this is relatively straightforward result as expected due to the higher degree of freedoms in the design parameters of REG. A more interesting investigation can be made regarding the trade-off between the level of complexity of the traffic management regime and the potential increase in the network capacity reliability.

4.2 Test with the Kobe Network

The proposed algorithm is further tested with the network of the Kobe city in Japan, see Fig. 5. The network consists of 140 directed links, 42 nodes and 8 centroids (56 OD pairs). γ_a is set to be 0.05 for all links in this test. The values of the capacity reliability for different $\overline{\mu}$ are obtained by the MC simulation of 50 runs. To show the effect of area-based traffic regulation, three scenarios are assumed;

Scenario 1: *Whole area regulation* which employs the same value of regulation rate for all OD pairs and is equivalent with the original definition of the capacity reliability as proposed in Chen et al. (2002),

Scenario 2: *Origin-based regulation* which applies the same value of regulation rate for each origin. This assumes that we can control the number of vehicles coming out from each origin,

Scenario 3: *OD-based regulation* in which the different regulation rate is enforced for each OD pair.

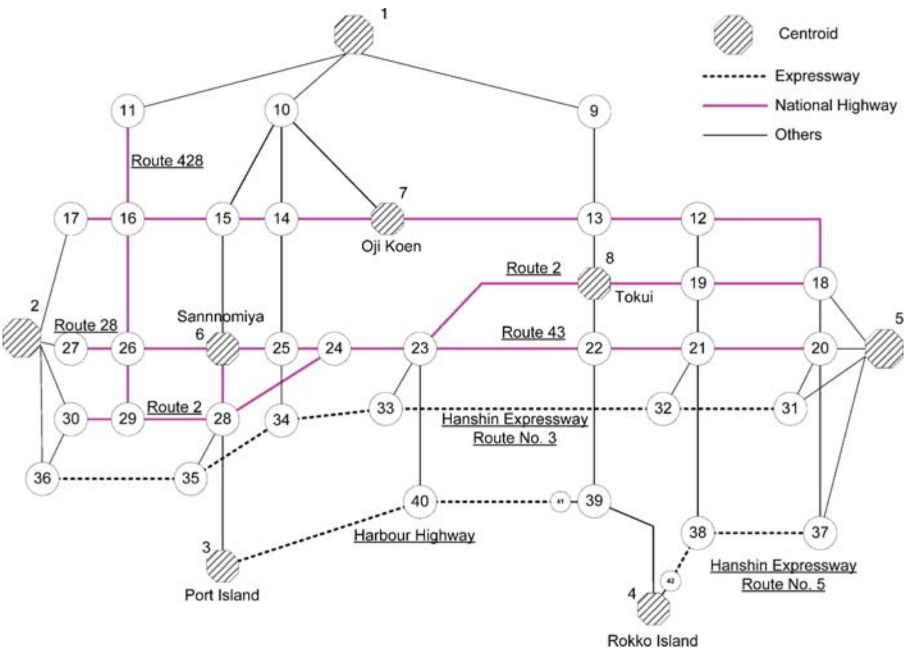


Fig. 5 Kobe test network

Figure 6 illustrates the calculation result of capacity reliability by different values of the threshold and scenarios. The vertical axis shows the traffic volume that the network can accommodate. The traffic volume that the network can accommodate with the capacity reliability of 0.9 is 38,530 for scenario 1, 85,378 for scenario 2 and 87,835 for scenario 3. From the tests, the OD based scheme

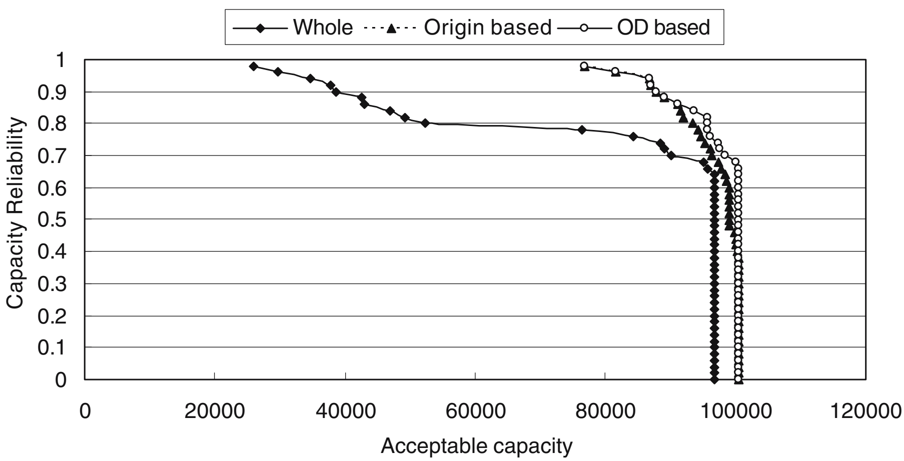


Fig. 6 Capacity reliability by different regulations

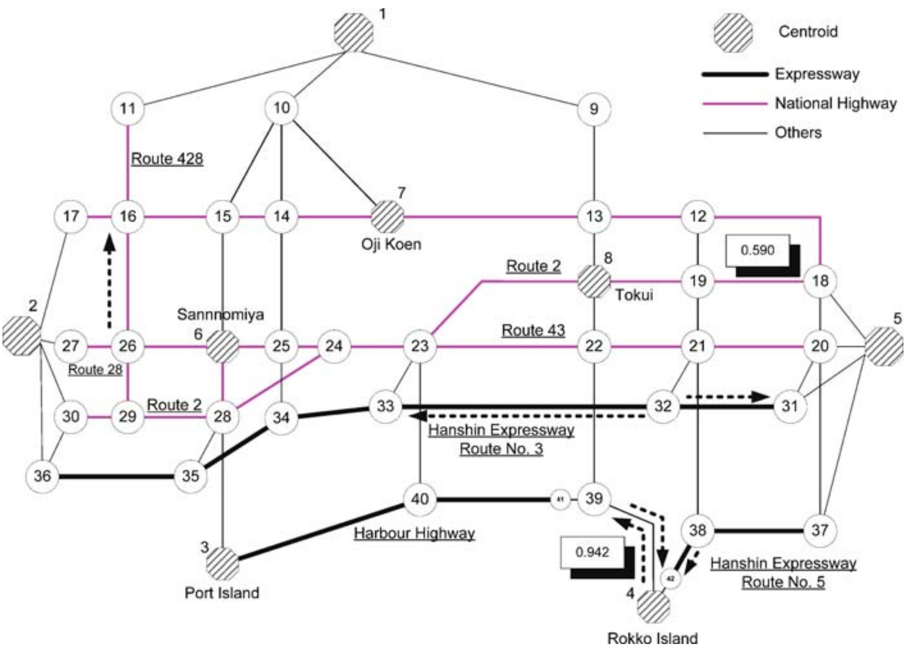


Fig. 7 Links with the flows equal to link capacities in a test with the Kobe network

generally performs best. With the lower acceptable level of demand in the network, the difference between capacity reliability indices of the whole area and OD based regulations becomes smaller. In contrast, the reliability indices of the origin based and OD based regulations are closer when the acceptable level of demand is lower. In general, the result suggests that the network capacity can be improved substantially by applying the traffic regulation.

Figure 7 and Table 1 illustrates one of calculations to show some detail result. In the Fig. 7, dotted arrow-lines highlight the links with the traffic volumes equal to the link capacities. The locations of the saturated links were same for all scenarios implying that these links are critical for ensuring a certain level of network

Table 1 Results of the optimal regulation rate for each scenario with the Kobe network

Origins	Whole	Origin-based	OD-based							
			1	2	3	4	5	6	7	8
1	0.83	1.00	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2		0.83	1.00	–	1.00	1.00	1.00	1.00	1.00	0.78
3		1.00	1.00	1.00	–	1.00	1.00	1.00	1.00	1.00
4		1.00	1.00	0.00	1.00	–	1.00	1.00	1.00	1.00
5		1.00	1.00	1.00	1.00	1.00	–	1.00	1.00	1.00
6		1.00	1.00	1.00	1.00	1.00	1.00	–	1.00	1.00
7		1.00	1.00	0.98	1.00	1.00	1.00	1.00	–	1.00
8		1.00	1.00	0.00	1.00	1.00	1.00	1.00	1.00	–

capacity. The rectangles and the contained values mark the degraded links and their rates of degradation. In this example, the capacity degradation of the link from nodes 4 to 39 decreases the total network capacity substantially. This link is the only outgoing link from zone 4 which is not the case for the other zones. Thus, the degradation on this link should inevitably decrease the level of demand from zone 4 which can enter the network.

In scenario 1, only 83% of the original demand can be accepted. In scenario 2, travel demands from all origins except that from origin 2 can be accommodated. In this case, applying the origin-based traffic regulation increases the network capacity from 84,277 (from the test with the whole area regulation) to 96,916. If OD-based traffic regulation (Scenario 3) can be implemented, the network capacity can be further increased to 98,635. In this case, the OD pairs with the suppressed demand levels are (4,2), (7,2), (8,2) and (2,8) which are all related to the traffic originated and destined at zone 2. In particular, the regulation rate of OD pair (4,2) and (8,2) are set to be zero. This implies that an efficient traffic regulation scheme does not necessarily involve many OD pairs in the network. However, this result can be highly subject to the network and demand configuration. Nevertheless, this result highlights the benefit of using this kind of analysis to detect the most important travel movements or links for ensuring a certain level of network capacity reliability.

5 Conclusions

The road network becomes extremely important after the major disaster. This is due to the decoupled effect of the degraded level of the link capacity and the sudden increase in the number of short-trips made by private cars to access goods and necessary life recovering activities as the systems of the other modes of transport can be more disrupted than the road network. Under such a degraded condition, the network manager may have to implement a form of traffic regulation to ensure a certain level of service (to avoid congestion). One measure to evaluate the performance of different traffic management schemes is the capacity reliability.

In this paper, the capacity reliability index refers to the probability of a certain traffic regulation measure to induce an acceptable level of travel demand in the network without violating the link capacities (possibly degraded). For a given state of the link capacities in the network, the problem of evaluating optimal traffic regulation parameters and the associated level of traffic demand allowed in the network can be formulated as a Network Design Problem. The concept of Probit SUE was introduced in the paper to represent travellers' route choices.

The method of sensitivity analysis was then proposed for the calculation of the derivative of the SUE link flows with respect to the traffic regulation parameters governing the level of travel demand for a certain movement. This derivative can then be used in any optimisation algorithm to solve the optimal traffic regulation problem. This problem is then integrated with the method of Monte-Carlo simulation which will randomly generate different states of the network (i.e., link capacities) from given statistical parameters of the possibility of each link to be disrupted. This method can be used to evaluate the capacity reliability index.

The algorithm was then tested with the five-link network and the network of the Kobe city in Japan. Different tests with different degrees of freedom of the traffic regulation parameters were carried out. Generally, the results from the tests with both network suggested a possible higher level of network capacity reliability with the regulation scheme with a higher degree of freedom (e.g., the scheme applying OD based traffic regulation has a higher degree of freedom than the whole area traffic regulation scheme). However, it is also found that an efficient control of the travel demand in the network to improve its capacity is not necessarily involved with a high proportion of the trips in the network. In the test with the Kobe network, mainly the trips associated with zone 2 were controlled under the OD-based regulation scheme. However, this result may depend largely on the network and demand configuration. Future research should investigate this pattern. In addition, a problem of optimal network improvement to improve the network capacity reliability is also an interesting topic for further investigation.

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References

Athukorala PC, Resosudarmo BP (2005) The Indian Ocean tsunami: economics impact, disaster management and lessons, Working Paper in Trade and Development No 2005/05, Division of Economics, the Australian National University

Bazaraa MS, Sherali HD, Shetty CM (1993) Nonlinear programming: theory and algorithms. John Wiley & Sons, Inc., New York

Bell MGH (1999) Measuring network reliability: a game theoretic approach. J Adv Transp 33(2): 135–146

Chen A, Yang H, Lo HK, Tang WH (2002) Capacity reliability of a road network: an assessment methodology and numerical results. Transp Res, Part B: Methodol 36(3):225–252

Chi-Chi Reconnaissance Team (2000) "Event report: Chi-CHi, Taiwan earthquake." Risk Management Solutions, California, USA

Clark SD, Watling DP (2002) Sensitivity analysis of the probit-based stochastic user equilibrium assignment model. Transp Res, Part B: Methodol 36(7):617–635

Connors R, Sumalee A, Watling DP (2006a) Variable demand probit-based network design problem: implicit programming approach. Transp Res, Part B: Methodol. Submitted

Connors RD, Sumalee A, Watling DP (2006b) Sensitivity analysis of the variable demand probit stochastic user equilibrium with multiple user-classes. Transp Res, Part B: Methodol. Submitted

D'Este GM, Taylor MAP (2003) Network vulnerability: an approach to reliability analysis at the level of national strategic transport networks. In: Bell MGH, Iida Y (eds.) The network reliability of transport. Pergamon, Oxford

Du ZP, Nicholson AJ (1997) Degradable transportation systems: sensitivity and reliability analysis. Transp Res, B: Methodol 31(3):225–237

IATSS, Research Report (2000) Study on personal passenger car traffic regulation following the great earthquake disaster (in Japanese)

Kurauchi F, Iida Y (1998) Study on origin/destination flow fluctuations in the period following the Great Hansin-Awaji earthquake. IATSS Rev 23(3):146–154 (in Japanese)

Mendell NR, Elston RC (1974) Multifactorial qualitative traits: genetic analysis and prediction of recurrence risks. Biometrics 30:41–57

Rosa A (2003) Probit based methods in traffic assignment and discrete choice modelling, PhD thesis, Napier University

Sheffi Y (1985) Urban transportation networks: equilibrium analysis with mathematical programming methods. Prentice-Hall, Englewood Cliffs, New Jersey

Sumalee A, Connors R, Watling DP (2006) Optimal toll design problem with improved behavioural equilibrium model: the case of Probit model. In: Lawphongpanich S, Hearn DW, Smith MJ (eds.) Mathematical and computational models for congestion charging. Springer, Berlin Heidelberg New York