ASSESSING TRAVEL TIME RELIABILITY OF ROAD NETWORKS CONSIDERING DAY-TO-DAY TRAVEL VARIATIONS

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Abstract: As the demands and needs of society for quality become more sophisticated, road networks are also expected to provide better service in terms of the stability and predictability of travel time. Day-to-day travel variations are one of significant sources of road networks' uncertainty and unpredictability. This paper suggests an approach of investigating the effect of the day-to-day travel variations of travelers on travel time reliability through stochastic process models of traffic assignment. Numerical examples are provided to illustrate the application of the proposed approach and some preliminary observations are presented to give us insight on how to ensure the network reliability under recurrent congestions.

Key Words: network reliability, day-to-day travel variations, stochastic process models

1. INTRODUCTION

More and more transportation professionals have recently highlighted the research on the reliability analysis of transport networks (see, Lam, 1999). Although earlier work has been done from the motivation of disaster mitigation (e.g., Wakabayashi and Iida, 1992; Du and Nicholson, 1997; and Asakura, 1999), later attempts have also been made to improve network reliability under routine operation conditions. The reason is that, as the demands and needs of society for quality become more sophisticated, road networks are also expected to provide better service in terms of the stability and predictability of travel time. A recent survey (Parkhurst et al., 1992) confirmed that one of the most common concerns of travelers is unreliability and the consequent variability and unpredictability of travel times. An unexpected delay may result in considerable loss to the transport users. The transport system should ensure the travelers to arrive their destinations as their schedules. However, in the normal daily operations, there are many sources of disruption, ranging from irregular and random incidents, like earthquake, flood, adverse weather, traffic accidents, breakdowns, signal failures, roadworks etc, to regular fluctuations of travel demand in times of day, days of the week, and seasons of the year (Taylor, 1999). To the aim of minimizing the disruption, assessment methods and tools are needed as pre-requisite, because it could help us with better understanding of the mechanism of performance reliability and thus give us more hints to ensure the network reliability.

Road network reliability problems are rooted in the uncertainty of traffic. It is difficult and impractical to model at a sufficiently microscopic level to imbue each source of uncertainty. Our approach is to model main sources separately and then evaluate their effects on reliability. Most of previous attentions have been given to formulate the uncertainty associated with the supply side (e.g., Chen et al., 1999; Yin and Ieda, 2000). Day-to-day travel variations are another significant source of the uncertainty associated with the demand side. Lam and Xu (1999) and Bell and Cassir (1999) evaluated the effect of daily fluctuation of travel demand on network reliability by assuming that travel demand was stochastic following the normal distribution and concluded that the larger the variance of travel demand was, the less reliable the network would be. However, day-to-day travel variations could be attributed to not only variations of travelers' trip generation behavior (the fluctuation of travel demand), but also variations of route choice behaviors among travelers and within travelers themselves. So far, how such variations affect network reliability is under-researched, and thus becomes the main research purpose of this paper. Be aware that different with the stochastic process (SP) traffic assignment model used in this paper, Watling (2000) proposed a second order stochastic network equilibrium model for the same aim. Besides, the effect of stochastic capacities of links has also been tackled in his study.

The remainder of the paper is organized as follows: Section 2 discusses briefly the road network reliability problem and then identifies the effect of day-to-day travel variations on network reliability. Section 3 describes how to model day-to-day travel variations. The SP models of traffic assignment suggested by Cascetta, (1989) and Watling (1996, 1999) are found very appropriate for our research purpose. Section 4 consequently applies such SP models to assess road network reliability, specifically travel time reliability by two numerical examples and then presents some calculation observations. The final section provides a summary and identifies directions for future research.

2. ROAD NETWORK RELIABILITY PROBLEM

Reliability is defined as the ability of an item to perform a required function, under given environmental and operational conditions and for a stated period of time (Hoyland and Rausand, 1994). Regarding road networks, the operational conditions could be normal and abnormal (after some exceptional disasters), where the following requirements should be satisfied:

1) After major exceptional events, like serious natural disasters, huge accidents, the connectivity and certain capacity between origin-destination (OD) pairs should be guaranteed so that people and goods can be transported for relief works;
2) In case of normal daily operations, road networks should ensure people and goods overcome the friction of geographical space efficiently and predictably even there are so many sources of disruption to road network system causing recurrent and nonrecurrent congestion.

Correspondingly, the reliability analysis of road networks could be divided into two dimensions: 'pure network' analysis and 'flow network' analysis (Nicholson and Du, 1997; and Asakura, 1999). The 'pure network' reliability analysis is applied to the situation of major exceptional events, comprising connectivity analysis (two-terminal, *k*-terminal and network connectivity) and capacity reliability analysis. It only focuses on the physical structure of the network and might be the earliest topic studied in transport network reliability and also has been widely and deeply studied in the field of telecommunications. In contrast, the 'flow network' reliability analysis is unique in the transportation field because it has to allow for the interaction between network performance and travel demand, travel decision-making behaviors of travelers, and the state of traffic information. 'Flow network' reliability could also be divided into two categories: terminal reliability and network performance reliability, where the former investigates the reliability between OD pairs while the latter emphasizes the performance of road network as a whole. For a more detailed review on road network reliability research, the reader may refer to Yin and Ieda (2000) and Lam and Zhang (2000).

Travel time reliability might be the most direct and widely employed concept in road network reliability. It is defined as the probability that a trip will arrive at its destination within a given threshold (Iida, 1999), described as follows:

$$R^{rs} = \Pr(t^{rs} \le m) \tag{1}$$

where, R^{rs} = the travel time reliability between OD pair *r-s;* t^{rs} = the minimal travel time between OD pair *r-s*; *m* = some given threshold.

Generally, it is computation-burdensome to obtain the probability distribution of travel time needed in Eq.(1). We still have two alternatives: one is to estimate only the mean and variance of travel times and then employ Chebyshev's inequality to estimate the travel time reliability, given as:

$$\Pr\left\{\left|t^{rs} - \mu^{rs}\right| < \varepsilon\right\} \ge 1 - \frac{{\sigma^{rs}}^2}{\varepsilon} \tag{2}$$

where, μ^{rs} = the expected value of travel time between OD pair *r-s*; ${\sigma^{rs}}^2$ = the variance of travel time; ε = any positive value of interest. The other is to employ directly variances or standard deviations (s.d.) of travel times as an index of travel time reliability, as Bell and Cassir (1999) did.

The above measures are suggested for terminal or OD pair reliability. In many cases, in order to evaluate transport policies that aim to improve the network reliability as a whole, a network-wide measure is needed. In this paper, we define it as the average travel time deviation per trip, illustrating the travel time variation that each traveler possibly experiences in one of his or her trips, given as:

$$R = \frac{\sum_{rs}\sum_{k} f_k^{rs} \cdot \sigma_k^{rs}}{\sum_{rs} q^{rs}} \tag{3}$$

where, f_k^{rs} = the flow on path *k* between OD pair *rs*; σ_k^{rs} = the standard deviation of travel time on path *k* between OD pair *rs* and q^{rs} = the demand between OD pair *rs*. Note that another network-wide measure can be defined as the ratio of the above index to the network average travel time, implying the magnitude of the variability of network travel time.

In this paper, our main research concern is to examine how day-to-day travel variations affect travel time reliability. As Hanson and Huff (1988) stated, day-to-day total travel variations could be decomposed into two parts, 1) interpersonal variations, attributable to differences between individuals and 2) intrapersonal day-to-day variations, attributable to differences within individuals over time. Partially owing to these interpersonal and intrapersonal variations, network traffic condition is changing day-to-day and thus unpredictable for travelers. For assessing road network reliability, it is necessary to model these two kinds of variations first.

3. MODELING DAY-TO-DAY TRAVEL VARIATIONS

Traditional traffic assignment models, both within-day static and dynamic, have been formulated following an equilibrium approach in which a state ensuring internal consistency between demand and cost is sought. However, such equilibrium analysis cannot simulate intrapersonal day-to-day variations, because it assumes that traffic volumes on roadways are likely to be at or near their equilibrium values. In other words, it is assumed that equilibrium is stable (Horowitz, 1984). Furthermore, the equilibrium analysis does not model explicitly travelers' memory and learning process.

Day-to-day dynamic process models provide essentially tools for modeling the above interpersonal differences and intrapersonal day-to-day variations, where interpersonal differences are modeled by random utility model and intrapersonal day-to-day variations are modeled by the memory-based learning mechanism and the corresponding travel choices. There are two types of day-to-day dynamic models suggested in the literature, namely deterministic process models and SP models (Cantarella and Cascetta, 1995). Deterministic process models, based on non-linear dynamic system theory, can analyze the asymptotic behavior of the system. They are also used to study equilibrium properties since the equilibrium state can be seen as a fixed-point attractor of a deterministic process under some hypotheses on travelers' learning mechanisms and switching behaviors. Stochastic process models, based on stochastic process theory, can estimate the stationary probability distribution of system states, say, path flows or costs. It is found that SP models are more suitable for our research purposes because we are more concerned about the possible variance of traffic conditions of road network than how the system converges to an equilibrium state. If deterministic process models reach one stable equilibrium state, the flows and costs in subsequent periods will never change. However, in SP models, flows are considered variable over time by the 'nature' of the underlying process determining them. That means, the generated flows will continue to vary, even when the stationary stage is reached. Therefore, SP models allow an explicit simulation of the intrinsic randomness of both demand and supply and the deterministic process models should be seen as an approximation of SP models (Cantarella and Cascetta, 1995).

SP traffic assignment models will be simply described below, based on the previous work by Cascetta (1989) and Watling (1996, 1999). Consider a general road network where link travel costs are function of link traffic flows. In order to study the evolution of the network system over a sequence of days ..., *t*-1, *t*, *t*+1, ..., the state occupied by the system in each day is defined by the path flow vector **F** with dimension equal to the total number of feasible acyclic paths in the network. Likewise, system states can also be defined in path choice vector space and link flow space with different level of aggregation. See Cascetta (1989) for a discussion of these variants and conditions for their equivalence. Because of the interpersonal and intrapersonal travel variations, it can be assumed that the path traffic flow at day *t* is discrete random variables. Consequently the evolution of road networks over different days is the realization of stochastic process with discrete time and state spaces.

To ensure that the stochastic process achieves a unique stationary or steady-state probability distribution and is ergodic, further assumptions are made regarding all potential travelers as follows:

1) All potential travelers moving between the same OD pair *(r,s)* have the same set of "feasible" path K_{rs}. Meanwhile, all potential travelers can decide independently whether to travel or not in each day with a constant probability q. This implies that the travel demand on any day follows a binomial distribution. It is noted that the no-trip option can be represented as a "dummy" path between OD pair, included in K_{rs}.

2) All travelers are rational decision makers. At each day *t*, they associate a perceived path travel costs $\psi_k^{rs}(t)$ to each alternative path and choose so as to minimize this cost. However, because of the interpersonal variations of "taste", $\psi_k^{rs}(t)$ could be deemed as random variables with the mean value $\eta_k^{rs}(t)$

$$\psi_k^{rs}(t) = \eta_k^{rs}(t) + \varepsilon_k^{rs}(t) \tag{4}$$

Based on the random utility theory (e.g., Sheffi, 1985), the probability choosing the *k*th path is given by

$$p_k^{rs}(t) = \Pr(\psi_k^{rs}(t) \le \psi_l^{rs}(t), \forall l \in K_{rs}) \tag{5}$$

As we know, if the perceived travel costs $\psi_k^{rs}(t)$ are assumed to be normally distributed, $\{p_k^{rs}(\eta^{rs}(t))\}$ follows a probit model while Gumbel distributed, $\{p_k^{rs}(\eta^{rs}(t))\}$ may follow a logit model. Other choice models can also be applied here.

3) All travelers have the same information acquisition (learning) mechanism. As we know, travelers do not know in advance the actual costs they will experience during the trip. Thus they make their choices according to perceived path costs, resulting from their memory and learning processes. Personal experience is usually complemented by information exchanged with other travelers and possibly provided by an information system. Therefore, it is rational to assume that at each day *t*, they base their choices on a weighted average of costs actually incurred in a finite number (*m*) of previous days:

$$\eta_k^{rs}(t) = \sum_{i=1}^{m}\left[w_i\left(c_k^{rs}(\mathbf{F}^{t-i}) + \alpha_k^{rs}(t-i)\right)\right] \tag{6}$$

Where $c_k^{rs}(\mathbf{F}^{t-i})$ means the average path costs at day t-i, $\alpha_k^{rs}(t-i)$ is the determination of a random variable taking account into fluctuations of actual costs around the average value $c_k^{rs}(\mathbf{F}^{t-i})$ and w_i is a weight value.

Combining Eq. (4) and Eq. (6) yields:

$$\psi_k^{rs}(t) = \sum_{i=1}^{m} w_i c_k^{rs}(\mathbf{F}^{t-i}) + \theta_k^{rs}(t) \tag{7}$$

The random term $\theta_k^{rs}(t)$ is obtained as the weighted sum of random variables ε_k^{rs} and α_k^{rs}. It is noted that with Eq. (5) and (7), the path choice probabilities (the system state) on day t are dependent on the previous m days' travel conditions (system states).

With above assumptions, Cascetta (1989) has proved that the stochastic process will possess a unique stationary probability distribution of path flows because the process is a m-dependent irreducible Markov chain with a time-homogeneous transition probability matrix. That implies regardless of the starting conditions, elapsed days and link cost functions, path flows prevailing on the networks over time will follow this stationary probability distribution. Moreover, the stochastic process is ergodic. That implies that the steady-state probability may be estimated from a single realization of the process.

Two approaches, analytic and simulation could be applied to obtain the stationary probability distribution or mean and variance of flows and costs. The former can only be used for small-scale networks with logit-based path choice model and small m. In this case, the one-step transition probability matrix A will not have an untreatable dimension and the elements can be calculated explicitly with the logit choice model. Then, the stationary distribution Ψ can be determined by solving the following fixed-point problem with Gaussian elimination:

$$\Psi = A \cdot \Psi \tag{8}$$

For larger problems, Monte Carlo simulation approach is available for pseudo-random realization of the stochastic process through which the mean and second-order moments of link flows (costs) may be estimated. It is noted that such Monte Carlo simulation technique is similar to that for the traditional probit-based stochastic equilibrium models (Sheffi, 1985) and will not yield much more computation burden. It is:

Step 1. Initiation. Set day $t=0$. Assume some initial mean perceived link costs.

Step 2. Increment t. Based on the current mean perceived cost, simulate path choice of travelers via path choice models (5) and then compute resulting link flows;

Step 3. Calculate the average link volumes and standard variation over all iterations.

Step 4. Convergence check. If not, compute average perceived cost by using last 'm' iteration flows via Eq. (7) and then go to Step 2.

When calculating the average and standard deviation, some initial days' results should be discarded until the stationary hypothesis is not rejected by suitable statistical tests.

4. APPLICATION OF SP MODELS TO NETWORK RELIABILITY ANALYSIS

As mentioned above, an unreliable network can be partially attributed to the uncertainty associated with the demand side, that is, day-to-day travel variations. Through the above SP model, interpersonal variations and intrapersonal day-to-day variations can be formulated. Once the stationary probability distribution is achieved, we can estimate the mean and variance of travel times. Consequently, based on the definition given in Section 2, travel time reliability under recurrent congestions can be assessed. One of the aims of reliability research is to seek solutions to improve or guarantee the road network reliability. Confronted with uncertainty caused by travel variations, although not much could be done to decrease their scale, it should be possible for us to figure out how to make the network more certain and predictable. In this section, we evaluated whether traditional congestion-relieving policies improve travel time reliability under recurrent congestions or not.

The first example was a two-link, single OD pair network taken from Cascetta (1989). The following link travel time function was used

$$t_a(x_a) = t_a^0\left(1 + 2.6\cdot\left(\frac{x_a}{c_a}\right)^4\right), a = 1,2 \tag{9}$$

Link free travel time t_a^0 for link 1 and 2 were 7 and 12 separately. In this example, we used the logit path choice model with dispersion parameter equal to 0.3, and assumed that the learning mechanism was based on '*m*' previous costs with uniform weights, and the travel demand was fixed without daily fluctuation. The computations were performed by the Monte Carlo simulation technique.

Firstly, we assumed both links have capacity of 37.5, and $m=10$, then the relationship between OD travel demand and travel time reliability were examined. The results are given in Table 1, and depicted in Figure 1. Secondly, we fixed OD travel demand as 50 and $m=10$, and changed the link capacity separately to examine the effect of link capacity. The results are given in Figure 2.

Table 1. OD Travel Demand versus Travel Time Reliability

OD	0	10	20	30	40	50	55	60	70
Average travel time s.d.	0.00	0.02	0.22	0.72	1.64	4.90	30.61	69.75	133.74
Average travel time	-	7.96	8.54	9.97	11.82	14.25	38.30	81.01	148.17
Ratio of s.d. to average time	-	0.003	0.025	0.072	0.139	0.344	0.799	0.861	0.903

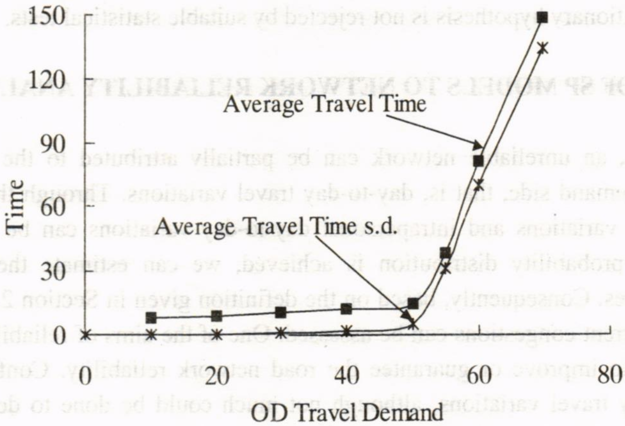

Figure 1. OD Travel Demand versus Travel Time Reliability

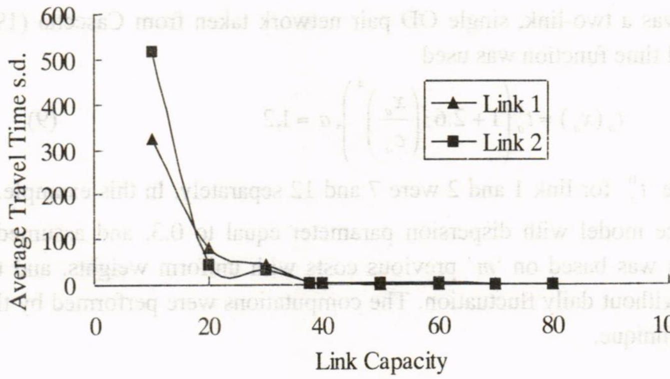

Figure 2. Link Capacity versus Travel Time Reliability

Results show that the travel time reliability has an exponential relationship with OD travel demand after some threshold value. This upward tendency is similar as that of travel time, shown in Figure 1. More experiments have been made and it is found that the value of threshold is dependent on the capacity of the link, and the relationship between traffic volume and speed on that link. Furthermore, it is illustrated in Table 1 that the ratio of travel time standard deviation to travel time is also increasing, which implies that the magnitude of travel demand impose more influence on travel time variation than on travel time. Likewise, the travel time reliability shows a similar but adverse relationship with link capacities in Figure 2. As a result, it is concluded that the traditional transport measures against congestions, like road expansion may also enhance network travel time reliability under recurrent congestions, even more efficiently.

Finally, we set the capacity for both links as 37.5, and OD travel demand as 50, and then examined the relationship between users' knowledge about the network conditions and travel time reliability. The value of m in Eq. (7) might be viewed as an index of the depth of travelers' knowledge about network traffic condition. A larger value of m might imply that travelers know much about the network evolution and then make their choices more rationally. Figure 3 gives the computation results. As expected, it presents a general tendency that the more travelers know about the network, the less variations will be caused by their own trip decisions. This observation offers us a preliminary idea that, although the greatest benefit of advanced traveler information systems (ATIS) is thought to come from non-recurrent congestion, providing information to travelers might also improve the travel time reliability under recurrent congestion. Certainly, a further detailed examination of this observation is needed.

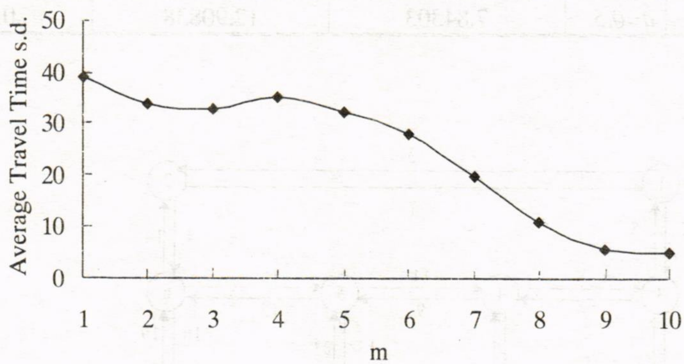

Figure 3. The Number of Previous Days' Knowledge versus Travel Time Reliability

The second example is more general and closer to the reality. The network was the medium-size Sioux Falls network, which included 14 centroids plus 10 normal nodes and 76 links, shown in Figure 4. The Bureau of Public Road (BPR) link travel time function was used in this example and the relevant network characteristics are presented respectively in Table 2. The probit path choice model was employed with variance parameter equal to 0.3 and in the learning mechanism 10 days' previous costs with uniform weights were used. Furthermore, we considered the daily fluctuation of travel demand by assuming all potential travelers decide independently whether to travel or not in each day with a constant probability q. In the calculations, we kept the average travel demand unchanged (two magnitude of the average travel demand: Case 1 is as given in Table 3, and Case 2 is four times of that in Table 3) and examined different combinations of the number of potential users and trip generation probability q, corresponding to different levels of demand variability. Computation results were given in Table 4 by the Monte Carlo simulation technique.

The results verified the conclusion drawn by Lam and Xu (1999) that the travel time reliability is reduced as the daily demand fluctuation increases. However, it is found that the travel demand fluctuation might not impose so much influence on travel time variability as commonly recognized. The travel time variability is more sensitive to the magnitude of travel demand.

Table 4. Results for Different Magnitude of Travel Demand and Their Fluctuation

		Average travel time s.d.	Average trip time	Ratio of s.d. to average time
OD demand (Case 1)	*q=1.0*	0.00432	6.94888	0.00062
	q=0.9	0.00435	6.94907	0.00062
	q=0.7	0.00450	6.95704	0.00065
	q=0.5	0.00453	6.94903	0.00065
OD demand (Case 2)	*q=1.0*	7.06124	12.65484	0.55798
	q=0.9	7.30548	12.73125	0.57383
	q=0.7	7.40247	12.76029	0.58012
	q=0.5	7.84303	12.90838	0.60759

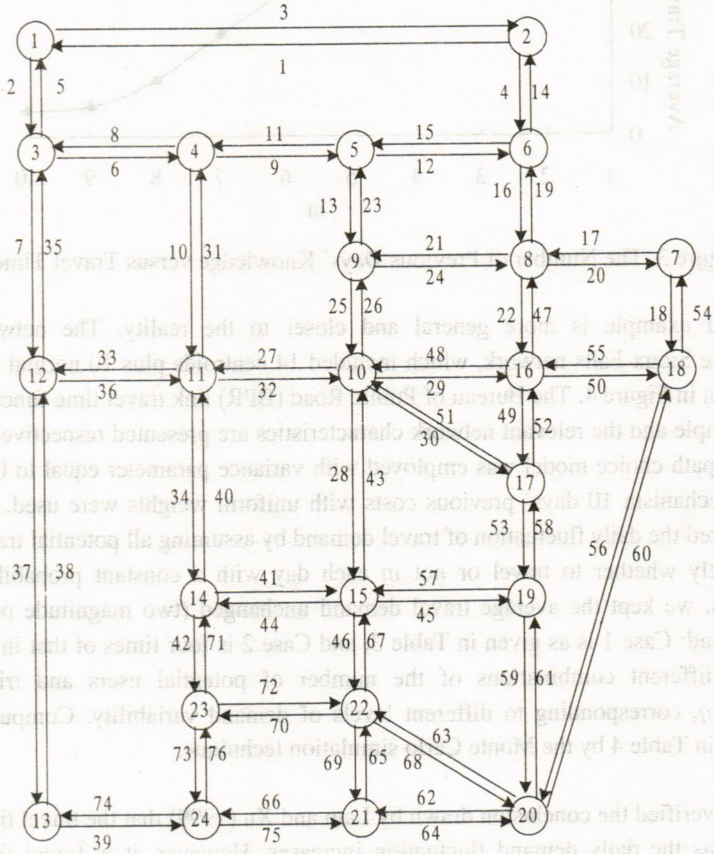

Figure 4. Sioux Falls Road Network

TABLE 2. Network Characteristics of Sioux Falls Network

Link a	t_a^0	c_a $(\times 10^3)$	Link a	t_a^0	c_a $(\times 10^3)$	Link a	t_a^0	c_a $(\times 10^3)$
1	3.6	6.02	27	3	20	53	1.2	9.65
2	2.4	9.01	28	3.6	27.02	54	1.2	46.81
3	3.6	12.02	29	3	10.27	55	1.8	39.36
4	3	15.92	30	4.2	9.99	56	2.4	8.11
5	2.4	46.81	31	3.6	9.82	57	2.4	4.42
6	2.4	34.22	32	3	20	58	1.2	9.65
7	2.4	46.81	33	3.6	9.82	59	2.4	10.01
8	2.4	25.82	34	2.4	9.75	60	2.4	8.11
9	1.2	28.25	35	2.4	46.81	61	2.4	6.05
10	3.6	9.04	36	3.6	9.82	62	3.6	10.12
11	1.2	46.85	37	1.8	51.8	63	3	10.15
12	2.4	13.86	38	1.8	51.8	64	3.6	10.12
13	3	10.52	39	2.4	10.18	65	1.2	10.46
14	3	9.92	40	2.4	9.75	66	1.8	9.77
15	2.4	9.9	41	3	10.26	67	2.4	20.63
16	1.2	21.62	42	2.4	9.85	68	3	10.15
17	1.8	15.68	43	3.6	27.02	69	1.2	10.46
18	1.2	46.81	44	3	10.26	70	2.4	10
19	1.2	9.8	45	2.4	9.64	71	2.4	9.85
20	1.8	15.68	46	2.4	20.63	72	2.4	10
21	2	10.1	47	3	10.09	73	1.2	10.16
22	3	10.09	48	3	10.27	74	2.4	11.38
23	3	20	49	1.2	10.46	75	1.8	9.77
24	2	10.1	50	1.8	39.36	76	1.2	10.16
25	1.8	27.83	51	4.2	9.99			
26	1.8	27.83	52	1.2	10.46			

Table 3. Average Peak-Hour OD Travel Demands

	1	2	4	5	10	11	13	14	15	19	20	21	22	24
1		600	600	600	490	500	570	450	430	410	270	270	350	340
2	600		570	590	500	510	410	430	430	590	270	310	310	270
4	600	570		600	490	490	430	410	380	370	280	290	270	370
5	600	590	600		520	440	410	400	370	330	370	370	430	270
10	490	500	490	520		610	410	450	600	530	430	410	440	270
11	500	510	490	440	610		430	600	500	430	340	280	500	470
13	570	410	430	410	410	430		400	390	310	270	280	310	600
14	450	430	410	400	450	600	400		600	520	430	400	410	520
15	430	430	380	370	600	500	390	600		600	580	520	600	410
19	410	590	370	330	530	430	310	520	600		600	500	500	370
20	270	270	280	370	430	340	270	440	580	600		600	600	280
21	270	310	290	370	410	280	280	400	520	500	600		600	600
22	350	310	270	430	440	500	310	410	600	500	600	600		520
24	340	270	370	270	270	470	600	520	410	370	280	600	520	

5. CONCLUSIONS

In this paper, we have presented an approach of assessing the road network reliability under recurrent congestions. By applying the SP models of traffic assignment suggested by Cascetta, (1989) and Watling (1996, 1999), the intrapersonal day-to-day travel variations and interpersonal travel differences have been modeled and then their effects on travel time reliability have been examined. Based on our limited numerical experiments, the following observations have been found:

1) Traditional congestion-relieving policies may more efficiently enhance network travel time reliability under recurrent congestions;
2) Providing information to travelers might also improve the travel time reliability under recurrent congestion;
3) The travel demand fluctuation might not impose so much influence on travel time variation as commonly recognized. The travel time variation is more sensitive to the magnitude of travel demand.

Future research work may further examine the effect of providing information to travelers on the network reliability under recurrent congestions. The state of network information plays an important role in determining the performance reliability of road networks. Therefore, some researchers (e.g., Iida, 1999) have suggested supplying information to drivers, via ATIS, to improve the performance reliability of road networks. One problem arises here is whether this alternative is really effective, and beneficial enough to compensate the cost of providing information or not. Although Asakura (1999) and Yin and Ieda (2001) have evaluated ATIS on improving reliability under non-recurrent congestion, the problem under recurrent congestions is still under-research. It is expected that the extended SP models could be competent to this task.

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