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Evaluation of incident management impacts using stochastic dynamic traffic assignment

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Abstract

In this paper, a dynamic traffic assignment (DTA) formulation with probabilistic capacity constraints is suggested in order to incorporate accident-induced random capacity reductions into evaluation of incident management strategies. For this purpose, a cell transmission model (CTM) based system optimal dynamic traffic assignment (SODTA) formulation is used as the underlying network model. Hypothetical scenarios are devised in which the potential incident management (IM) strategies are assumed to reduce either the average or the variation of the incident duration. For each case, a small scale Monte Carlo simulation is also performed and compared with the analytic results of the stochastic DTA model. It was shown that the stochastic DTA model not only provides the changes in total system travel time within the reliability measure, but it also provides the analytical results which requires significantly less computational burden. The model also incorporates the impacts of rerouting which is not possible with a queuing theory based analysis on a single link. The results also show that rather than reducing the average duration, comparable delay reductions can be achieved by reducing the variance while keeping the average accident duration unchanged. Hence, IM strategies, solely targeting average duration may be deemed not to be successful, yet, they may be an effective policy to reduce delay. Overall, the proposed model provides a computationally efficient network-wide analysis of incident induced delay without ignoring the highly stochastic nature of roadway incidents.

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Keywords: Dynamic Traffic Assignment; Stochastic Programming; Incident Management

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1. Introduction

Traffic incidents are one of the main causes of inefficiency in transportation networks. In case of a crash, safety concerns such as injuries and fatalities also arise along with economic impacts due to property damages. Vehicle emissions due to traffic incidents is also an environment sustainability issue. In order to reduce the adverse impacts of incidents, incident management strategies and traffic safety policies are developed to primarily avoid the occurrence of incidents, and secondly, to dissipate their adverse impacts once they happened.

The effectiveness of such strategies and policies can be assessed by comparing the actual impacts (e.g. delay, safety, economic cost) of a specific incident management policy/strategy that are measured before and after its implementation. Considering that most of the incident management and safety strategies involve major capital investments (especially in terms of ITS infrastructure), a prior estimation of the benefits of policies are thus necessary before their actual implementation. For that matter, simulation has been used as the primary tool for such evaluations (Fries et al. 2010; Ozbay et al. 2009; Ozbay and Bartin, 2003; Sisiopiku et al, 2007; Kamga et al., 2011).

Incidents are probabilistic events. Whether an incident would occur on a certain location, whether it is only a disablement or there will be a personal injury or just property damage, and how long it will take to clear a given incident are all random events. Realistic assessment of incident management strategies should address the stochasticity in the link capacities and impacts of incidents in a transportation network. In this paper, each incident is assumed to result in a temporary random capacity reduction. Accordingly, we approach the problem from a reliability perspective using dynamic traffic assignment as the evaluation tool. Cell transmission model (CTM) based system optimal dynamic traffic assignment (SODTA) formulation (Ziliaskopoulos, 2000) with probabilistic capacity constraints is used as the underlying model. Compared to traditional queuing theory based incident delay calculations, the CTM based approach allows a network-wide analysis in which the illustrated effects of alternative routes (Wirtz et al., 2005) are taken into account. In addition, the analytical stochastic programming approach is more efficient compared to computationally expensive sampling based simulation, e.g. Monte Carlo simulation. The proposed stochastic DTA model can incorporate the IM policy related changes in roadway capacity reduction distributions and calculate the network-wide impacts in terms of total system travel time. System optimal nature of the assignment also provides the best-case-scenario which can serve as a benchmark level to further assess the effectiveness after policy implementation.

2. Literature review

There are two main components of incident modeling which in turn define the characteristics of the random capacity reduction: frequency and duration. Frequency (or occurrence) of an incident is probabilistic in nature. An incident can happen due to various reasons which cannot be deterministically predicted, i.e. disablement due to mechanical malfunction, flat tire, accident due to human error. Duration of an incident also varies based on the type of incident (disablement, property damage, injury/fatality, availability of response vehicles etc.) and different average values are reported for different regions and facility type, e.g. freeway vs. arterial (Yazici et al., 2010). As a result of the variance in incident durations, researchers suggest using probability distribution to model the distribution of incident durations, e.g. Lognormal (Golob et al, 1987; Guiliano, 1989;Garib et al., 1997), Log-Logistic (Jones et al., 1991; Wu et al., 1998), Gaussian (Jones et al., 1991; Wu et al., 1998), Weibull (Nam and Mannering, 2000).

The past literature recognize that the traffic flow capacity is a stochastic variable already without accounting the incidents (Brilon et al., 2007; Geistefeldt, 2011; Tu et al., 2010). Incidents introduce additional randomness on roadway capacity and traffic flow (Gursoy et al. 2008). Related to the nature of an incident (e.g. disability, property damage, injury/fatality) and location (e.g. disabled vehicle at the shoulder, lane that an accident occurred) the roadway capacity reduction also varies. Smith et al. (2003) studies the changes in traffic flow before and after multiple incidents. They suggest that the capacity reduction due to accidents should be modeled as a random variable. Based on the observations of single and two-lane blocking incident, beta distribution is proposed as the best probabilistic distribution to represent the incident induced capacity reduction. Knoop et al. (2008) also study the traffic flow during incident conditions and detect varying flow distributions, however no specific probability distribution is identified.

In terms of car accidents, incident management strategies (IMS) first aim to reduce the frequency of accidents by legal enforcement, suggesting safer geometric road designs etc. Once the accident happens, IMS aim to respond to the incident in quickest (response teams to come to the accident location as soon as possible), safest (having medical personnel for possible injury) and most effective manner (fast clearance of the accidents). These strategies directly impact the roadway flow capacity since lower response times result in significantly faster recovery of regular traffic flow (Wilmink and Immers, 1996. While doing those above, maintaining a smoother network flow is achieved by using variable message signs, route diversions and so on (Wirtz et al., 2005).

Incident management studies mainly focus on delay due to an “average” of different incident types and generalize the delay impacts for all incidents. Literature includes deterministic queuing models (Olmstead, 1999) and simulation (Wirtz et al., 2005) for calculating incident induced delay. As discussed in Olmstead (1999) and Li et al. (2006) the variability of incident duration cause misleading estimations of the delay, hence stochastic queuing models are also employed to address the randomness and variability in incident durations (Li et al., 2006). As the next step, measures are identified to evaluate the effectiveness of IMS. A CALTRANS report (CTC & Associates LLC. 2010) summarizes the measures which are used by the transportation agencies in the U.S. to assess the performance of IMS. Almost all agencies set forth future targets in terms of incident duration/clearance time such as maximum clearance time of 90 minutes for major accidents in California, non-injury accidents in 30 minutes and serious injuries in 60 minutes in Utah etc. Achievement of such performance measures requires additional investment and effort on better information flow and coordination of law enforcement, emergency responders, incident response teams, and tow trucks.

DTA models, especially SODTA model used in the current study, has been used particularly with its stochastic variants to analyze network flow under random impacts (Waller and Ziliaskopoulos, 2006; Yazici and Ozbay, 2007; Yazici and Ozbay, 2010; Do Chung et al. 2012; Sun et al. 2014; Li and Ozbay, 2014). Time dependent nature of incident occurrence and clearance, route diversions, and resulting delays make dynamic traffic assignment a suitable network-wide analysis tool. Peeta and Zhou (2002) study capacity uncertainty related with incidents in a DTA setup for use in online route guidance. The capacity reductions due to incidents are implemented as scenarios where the stochasticity is included in the occurrence of an incident. The solution of the traffic network is calculated for the mean O-D demand and the results are used to update the online routing information calculated via using several O-D demand realizations. A TRB report (Chiu et al., 2011) also mentions incident management as one of the areas of DTA applications and cites Palma and Marchal (2004), Sisiopiku et al. (2007); Wirtz et al. (2005) as some examples. Kamga et al. (2011) discuss that the impacts of incident delays are network-wide rather than confined to the link on which the incident occurred. Thus, an IMS' effectiveness should be assessed considering the broad network. Overall, the uncertainty of incidents and their impacts on link capacities and network flows exhibit a complex problem in terms of accurately assessing the effectiveness of incident management schemes. This paper aims to provide an analytical formulation to carry out such assessments considering car accidents/crashes.

3. Methodology

In this paper, CTM based SODTA model with probabilistic constraints (also called *chance constraints*) is used for assessing the network-wide impacts of incident management strategies. The original CTM based SODTA formulation (Ziliaskopoulos, 2010) assumes deterministic flow capacities in the network. The standard linear programming (LP) representation of the CTM based SODTA formulation and the formulation with individual probabilistic capacity constraints (which allows flow capacity to be random) are shown below:

$$
\begin{array}{cc}
\textit{Deterministic Formulation} & \textit{Stochastic Formulation} \\
\min \sum_t \sum_i x_i^t & \min \quad \sum_t \sum_i x_i^t \\
s.t. A_{eq} v = b_{eq} & s.t. \;\; A_{eq} v = b_{eq} \\
Av \le b & Av \le b \\
Tv \le \hat{Q} & P\left(T_k^{pr} v \le \phi_k\right) \ge p_k \;\; , k = 1, \dots, K^{pr} \\
x_i^t \ge 0,\ y_{ij}^t \ge 0, \forall (i,j) \in \xi, \forall t \in T & x_i^t,\ y_{ij}^t \ge 0,\ \ \forall (i,j) \in \xi,\ \ \forall t \in T
\end{array}
\tag{1}
$$

where x_i^t is the number of vehicles at cell i at time t; y_{ij}^t is the flow from cell i to cell j at time t; $v = \begin{bmatrix} x_i^t \\ y_{ij}^t \end{bmatrix}$ is the vector of system states; $\hat{Q}$ is the vector of time-expanded forms of all cell capacities (Q_i^t); T_k^{pr}: k[th] row of the matrix T^{pr}; A_{eq} and A are the matrices represent the inequality and equality constraints in CTM based SO DTA model; b_{eq} and b are the right hand side values corresponding to the aforementioned inequality and equality constraints; *t* is the time step along the assignment horizon of *T*.

Regarding the matrix dimensions, let there be R and S equality and inequality constraints respectively, and *K* capacity constraints, making *R*+*S*+*K*=*M* constraints in total and *N* decision variables. A_{eq} $(R\times V)$ and b_{eq} $(R\times 1)$ include the conservation of mass equations and the demand equation at source cells; A $(S\times N)$ and b $(S\times 1)$ represent inequality constraints other than capacity constraints; T $(K\times N)$ represents the capacity constraints with capacity vector $\hat{Q}(K\times 1)$. Since the constraints are defined for each time step, $\hat{Q}$ vector consists of time-expanded forms of all cell capacities (Q_i^t) in the network. An optimal solution with the probabilistic constraint $P(T_k^{pr}v \leq \phi_k) \geq p_k$ ensures that the probabilistic constraint would hold with probability p_k. The solution of the stochastic programming problem can be found by calculating deterministic equivalent of the probabilistic constraint, and substituting back into the LP. Deterministic equivalent of the constraint $P(T_k^{pr}v \leq \phi_k) \geq p_k$ is calculated as follows:

$$P(T_k^{pr}v \leq \phi_k) \geq p_k \rightarrow\ 1 - P(T_k^{pr}v > \phi_k) \geq p_k \rightarrow\ 1 - F_{\phi_k}(T_k^{pr}v) \geq p_k \rightarrow\ F_{\phi_k}(T_k^{pr}v) \leq 1 - p_k$$

$$\xRightarrow{Deterministic\ Equivalent\ Constraint} \quad T_k^{pr}v \leq F_{\phi_k}{}^{-1}(1 - p_k) \tag{2}$$

where F_{ϕ_k} and $F_{\phi_k}{}^{-1}$ are respectively the cumulative distribution function (CDF) and the quantile function (or inverse CDF) of the of the random variable (r.v.) ϕ_k. Once $F_{\phi_k}{}^{-1}(1 - p_k)$ is calculated, the problem can be solved as a regular deterministic LP. However, the existence of $F_{\phi_k}{}^{-1}$ and convexity of the LP after substituting the deterministic equivalent constraint are not always guaranteed. That being said, following section shows that the problem at hand exhibit the necessary features which allow the use of chance constraints for incident induced random capacity reductions.

3.1. Roadway Capacity Under Accident Conditions

In CTM based SODTA formulation, roadways are spatially divided into cells and the analysis is based on time intervals, thus flow capacities are allowed to vary spatio-temporally. Let the percentage capacity of a certain roadway section, say cell j, and a particular time, say t, is given by φ_j^t. An accident can happen at a certain location but once the accident is cleared, the capacity is restored back to "normal", non-accident conditions. For cell *j* to experience accident induced capacity reduction at time *t*, first, the accident has to happen at cell *j*. Second, the accident should occur at time $t_0 \leq t$ and still not cleared by time *t*. Then the magnitude of the reduction is a function of multiple factors ranging from the accident lane (e.g. middle lane in a 3-lane highway) to accident severity (e.g. an injury accident which requires ambulance and tow truck dispatch). In the current study, for simplicity, the roadway capacity is assumed to be 100% (full capacity) during regular ("non-accident") conditions. Let Y be the random variable (r.v.) for the percentage of remaining capacity during accident conditions, then:

$$\varphi_j^t = \begin{cases} 1 & \text{no accident} \\ Y & \text{accident conditions} \end{cases}$$

Let's define two events, E_1 and E_2, which are mutually exclusive (cannot happen at the same time, i.e. $E_1 \cap E_2 = \emptyset$) and collectively exhaustive (together cover the whole sample event space, i.e. $E_1 \cup E_2 = S$).

E_1 **:** Accident conditions are observed at cell *i* at time *t* (either happened at time *t*, or happened at $t_0 < t$ but still not cleared at time *t*)

E_2 **:** Accident conditions are NOT observed at cell *i* at time *t* (either not happened yet, or happened and cleared at $t_0 < t$)

Let the r.v. X has a probability distribution function (PDF) $f_Y(x)$ and a cumulative distribution function (CDF) $F_Y(x)$. Similarly, let φ_j^t has a PDF $f_{\varphi_j^t}(x)$ and a CDF $F_{\varphi_j^t}(x)$. Thus, $F_{\varphi_j^t}(x)$ is a mixture density of F_Y (under accident conditions) and F_Z which a unit mass for capacity (under non-accident conditions). Using the law of total probability, one can write:

$$F_{\varphi_j^t}(x) = F_Z(x) \times P(E_1) + F_Y(x) \times P(E_2) \tag{3}$$

where $F_Z(x) = \begin{cases} 0 & 0 \leq x < 1 \\ 1 & x = 1 \end{cases}$

Calculating the probabilities of E_1 and E_2 for an arbitrary spatio-temporal setup (e.g. accident occurrence on an arbitrary road stretch at an arbitrary time) is a difficult research question of its own right and it is out of the scope of the current paper. The relationship between the severity of the accident and accident duration may further complicate the problem. For the purposes of this study, accident is assumed to occur at a selected cell, at a certain time during peak hours and accident duration is assumed to be independent of the accident type. Thus, if an accident occurs on cell *j* at t_0=0, then the accident conditions are observed at cell *j* at time *t* only if the accident has not been cleared yet. In other words, when the accident location and time are given, E_1 and E_2 are simply defined by whether the accident is cleared by time *t*.

E_1 **:** Accident conditions are NOT observed (accident is cleared at time $t_1 < t$)

E_2 **:** Accident conditions are observed (accident is still not cleared at time *t*)

If the distribution of the accident duration θ is known, one can easily compute probabilities of events E_1 and E_2 for all $t \geq t_0$, i.e. $P(E_1) = P(t > \theta) = F_\theta(t) = q$ and $P(E_2) = P(t \leq \theta) = 1 - F_\theta(t) = 1 - q$, where F_θ is the CDF of the accident duration. Accordingly:

$$F_{\varphi_j^t}(x) = \begin{cases} (1-q) \times F_Y(x) & , 0 \leq x < 1 \\ 1 & , x = 1 \end{cases} \tag{4}$$

Once $F_{\varphi_j^t}(x)$ is calculated, the problem can be solved by substituting the deterministic equivalent of probabilistic constraints by using $F_{\varphi_j^t}^{-1}(\alpha)$. Nonetheless, $F_{\varphi_j^t}(x)$ has to be a log-concave density for the stochastic programming problem to be convex. $F_{\varphi_j^t}(x)$, as formulated above, is a linear function of the distribution $F_Y(x)$ and $F_{\varphi_j^t}(x)$'s log-concavity characteristics depends on $F_Y(x)$. Since distribution of the accident duration is only used to calculate "q", accident duration distribution does not affect the logconcavity of $F_{\varphi_j^t}(x)$

Findings on accident capacity distribution under accident conditions presented in a paper by Smith et al. (2003) are employed for $F_{\varphi_j^t}$. Smith et al. (2003) determined that probability of *capacity reduction* during accident conditions follows Beta distribution and provide empirical estimations for the reduction percentages. Probability density function for Beta distribution is $f(X;\alpha,\beta) = \frac{1}{B(\alpha,\beta)} X^{\alpha-1}(1-X)^{\beta-1}$, where $0 < X < 1$, α and β are the shape parameters and $B(\alpha,\beta)$ is the Beta function, $B(\alpha,\beta) = \int_0^1 u^{\alpha-1}(1-u)^{\beta-1}\,du$. If $X \sim Beta(\alpha,\beta)$ is the random variable that represents the capacity reduction percentage, then remaining capacity is $Y = 1 - X$. The probability density function of Y can calculated with the change of variable as:

$$f(Y;\alpha,\beta) = \frac{1}{B(\alpha,\beta)}(1-Y)^{\alpha-1}Y^{\beta-1} \tag{5}$$

In short, if $C_{reduction}$ follows $Beta\ (\boldsymbol{\alpha},\boldsymbol{\beta})$, then $C_{remaining} = 1 - C_{reduction}$ follows $Beta(\boldsymbol{\beta},\boldsymbol{\alpha})$. Hence:

$$F_{\varphi_j^t}(x) = \begin{cases} (1-q) \times Beta(x;\ a, b) & 0 \leq x < 1 \\ 1 & x = 1 \end{cases} \tag{6}$$

Beta distribution is one of the commonly known distributions with a log-concave density for $a \geq 1, b \geq 1$ (Prekopa, 1995). Since the log-concavity properties are preserved under linear transformations, $F_{\varphi_j^t}(x)$ is also log-concave, hence the stochastic programming problem is convex. Based on Castellacci (2012), the quantile function (or inverse CDF) $F_{\varphi_j^t}^{-1}(\epsilon)$ can be written as:

$$F_{\varphi_j^t}^{-1}(\epsilon) = \begin{cases} Beta^{-1}\left(\frac{\epsilon}{(1-q)}\right) & 0 \leq \epsilon < (1-q) \\ 1 & (1-q) \leq \epsilon \leq 1 \end{cases} \tag{7}$$

where $Beta^{-1}(\cdot)$ is the inverse CDF of Beta distribution. Once $F_{\varphi_j^t}^{-1}(\epsilon)$ is defined, it can be substituted in the chance constraint as previously discussed: $P\left(T_k^{pr} v \leq \phi_k\right) \geq p_k \rightarrow \;\; T_k^{pr} v \leq F_{\phi_k}{}^{-1}(1 - p_k)$

4. Numerical Example

The implementation of the model is performed for a network selected from New Jersey highways, namely US-1 and New Jersey Turnpike (NJTPK) for which the authors have accident duration data. The origin and the destination are assigned to be just before NJTPK exit #10 and just after NJTPK exit#13 where US-1 and NJTPK interchanges are at close proximity (Figure 1). The links between two roadways at each intersection are also included in the network. Hence, drivers can take either NJTPK (relatively faster) or US-1 (relatively slower) between the origin and the destination, and can also re-route along the way (through exits on NJTPK) in case there is an accident. The cell network constants are given in Table 1. For the analysis, the network demand is assumed to be 1.5 times of the combined flow capacity for NJTPK and US-1 for two hours. Instead of loading onto an empty network, the cell occupancy and flow after one hour are assigned for the network at time=0 in order to represent the rush hour traffic with congestion onset.

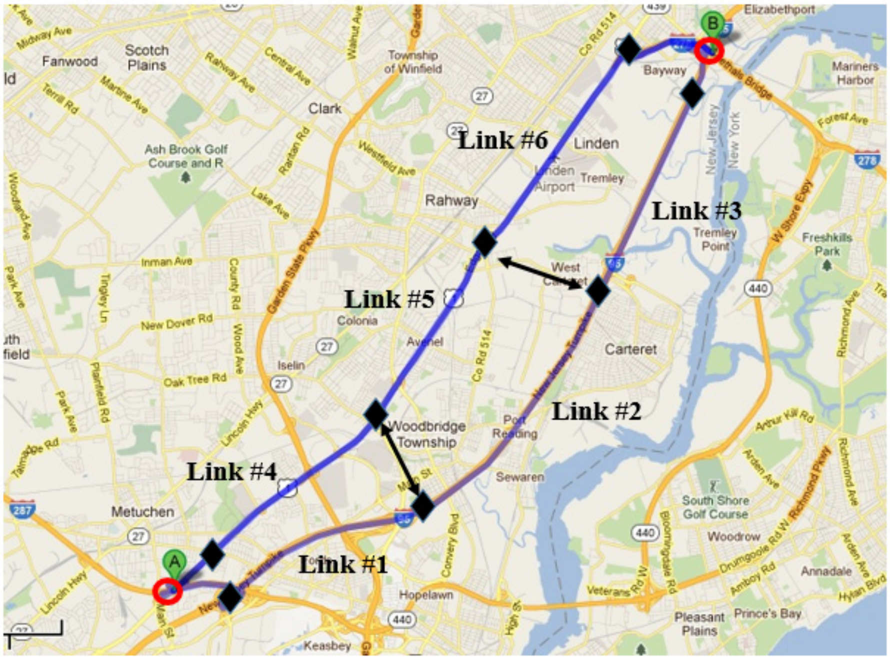

Figure 1 Selected Origin-Destination and Main Routes in NJ for the Case Study (Source: Google Maps)

Table 1 Time Invariant Cell Properties of the Test Network for Time Step = 30 seconds

	Cell Type			
	Source/ Destination	NJTPK	US-1	Interchange Connections
Free Flow Speed (mil/h)	-	60	50	40
Cell Length (miles)	-	0.500	0.416	0.333
Number of Lanes	-	6	3	2
Max Flow Capacity* (veh/hr)	Infinite	12960	6480	4320
Max Cell Flow (veh/time step)	Infinite	108	54	36
Max Cell Physical Capacity** (vehicles/cell)	Infinite	750	312	166
Ratio of v/w	-	5	5	5

* (2160 vphpl) x (Number of Lanes)

** (250 veh per mile) x (Cell Length) x (Number of Lanes)

The accident duration distributions are calculated based on best-fit on the Author's accident duration data for the modelled roadway section (Figure 2). Accident duration on NJTPK and US-1 are found to follow Weibull with parameters 60.30, 2.84 –Weibull(60.30, 2.84) – and Gamma(1.95413, 19.1325) respectively. Authors do not have site specific data for accident induced capacity reductions at NJTPK or US-1. Thus, capacity reduction distributions is assumed to follow Beta distribution based on Smith et al.'s (2003) findings, specifically Beta (6.83057, 4.05907) for capacity reduction for one lane out of three lanes blocked, which means that remaining capacity is distributed by Beta (4.05907, 6.83057).

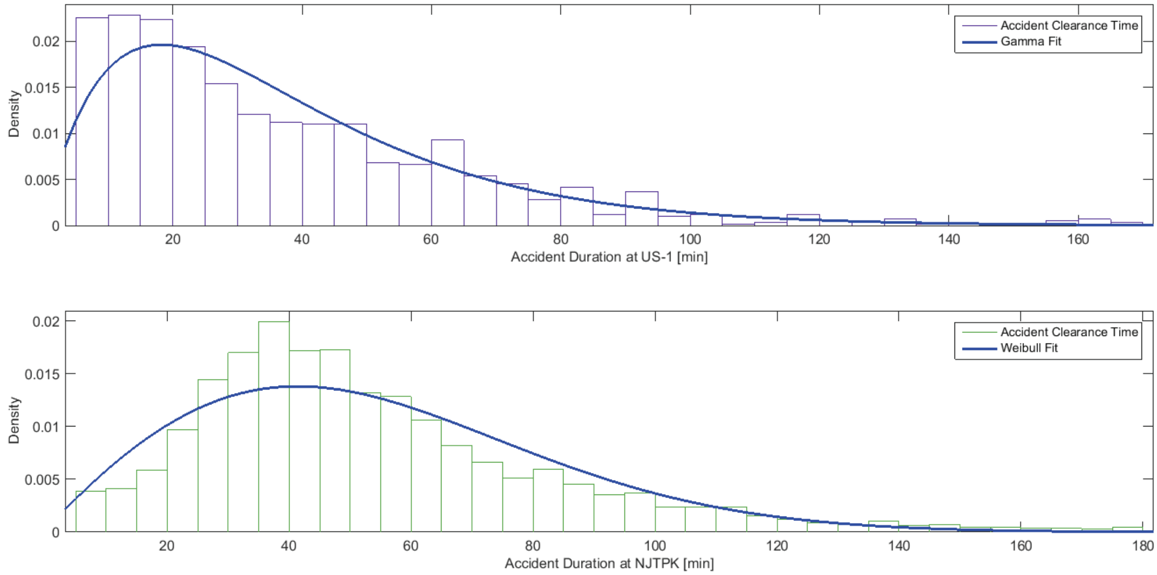

Figure 2 Probability Distribution Fit to Existing Accident Duration Data

Different incident management (IM) strategies may have different levels of impact on accident duration characteristics. For the numerical example, 5 different accident duration distribution scenarios are considered in order to cover potential IM impacts. Case#1 refers to the existing accident duration distribution. Cases #2 and #3 represents reduction in variance of the accident duration (-5 and -10 mins respectively) without affecting the mean. In cases #4 and #5, the variance stays the same but average duration decreases (-5 and -10 mins, respectively). In all cases, the distribution function is assumed to be the same (e.g. Weibull for NJTPK and gamma for US-1) and distribution parameters are adjusted to yield varying mean and variances. The hypothetical scenarios aim to illustrate the impacts of change in accident duration characteristics and the capabilities of the stochastic DTA model.

Table 2 and Table 3 show that decreases in both mean and standard deviation results in delay reductions as expected. The results also show that 5 minutes of decrease in standard deviation has more or less the same amount of impact as 5 minutes reduction in average duration (Case#2 vs. Case#4). This finding implies that not achieving a target of average accident duration reduction does not necessarily mean a failed policy as long as there is a reduction in variance. It should also be noted that as the accident location gets closer to the destination node, the delay due to the accident – albeit slightly – increases. Thus the network-wide analysis allows assessment of individual or simultaneous impacts of spatially varying IM strategies.

Table 2 Change in Total System Travel Time due to an Accident at NJTPK

Case	**Accident Duration**		**Percentage Increase in Total System Travel Time w.r.t. Accident Location**		
	Average	**Std. Dev.**	**Link#1**	**Link#2**	**Link#3**
Case #1	53.7	20.5	37.8%	39.0%	40.0%

Case #2	53.7	15.5	35.3%	36.4%	37.3%
Case #3	53.7	10.5	32.8%	33.8%	34.6%
Case #4	47.7	20.5	35.6%	36.7%	37.6%
Case #5	42.7	20.5	33.6%	34.2%	35.1%

Table 3 Change in Total System Travel Time due to an Accident at US-1

Case	**Accident Duration**		**Percentage Increase in Total System Travel Time w.r.t. Accident Location**		
	Average	**Std. Dev.**	**Link#4**	**Link#5**	**Link#6**
Case #1	37.4	26.7	15.9%	16.2%	16.8%
Case #2	37.4	21.7	14.8%	15.1%	15.7%
Case #3	37.4	16.7	13.7%	14.0%	14.5%
Case #4	32.4	26.7	14.6%	14.9%	15.5%
Case #5	27.4	26.7	13.3%	13.5%	14.1%

One of the main strengths of the stochastic DTA lies on its reliability based results, e.g. Table 2 and Table 3 show the improvements in total system travel time which is valid for 90% of the possible accident cases. One may argue that Monte Carlo simulation can also be considered as a probabilistic approach alternative. In order to provide a comparison with the stochastic model, CTM based SO DTA model is run for all five accident duration cases for an accident occurring on Link #2 (on NJTPK). For each case, 300 distinct scenarios with accidents on Link #2 with random durations are created and total system travel time for each random accident is calculated. Figure 3 shows the distribution of total system travel times based on the Monte Carlo simulation results for Cases #1, #3 and #5. Left hand side of chart shown on Figure 4(a) shows the average total system travel time and it clearly follows a consistently decreasing pattern where the decrease in average travel time has considerably more impact than the decrease in variance. This trend seems to contradict the findings of the stochastic DTA model both in terms of magnitude and trend. Meanwhile, middle chart on Figure 4(b) shows the 90% quantile of the total system travel time distribution which is more appropriate to compare with stochastic DTA results which is calculated with probabilistic constraint to hold 90% of the times. Although there is not a one-to-one match with stochastic DTA results, the 90% quantile figure reveals that reduction in variance only may yield similar results as reduction in average duration alone. There is a strange anomaly for Case #2 (increased total system travel time despite reduced variance), but it disappears on on Figure 4(c) which shows the 95% quantile results. This instable trend is potentially due to employing 300 accidents for each case which is a very small sample size for Monte Carlo simulation, yet the computational burden is still significant. In this sense, stochastic DTA provides an efficient methodology to calculate reliability bounds for the system wide performance with significantly lower computational burden.

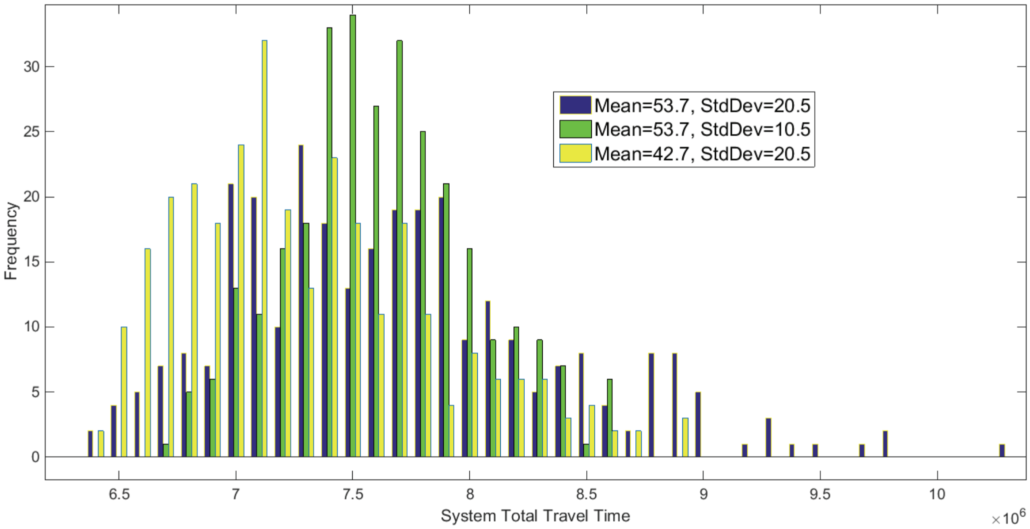

Figure 3 Total System Travel Time Distribution Based on Monte Carlo Analysis

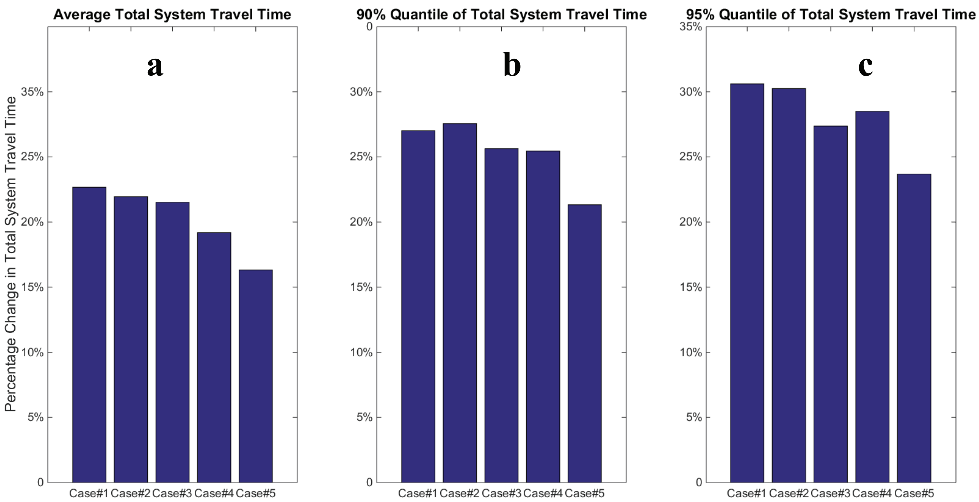

Figure 4 Overall Results of Monte Carlo Analysis for Each Case

5. Conclusion

In this paper, a dynamic traffic assignment (DTA) formulation with probabilistic capacity constraints was proposed in order to incorporate incident-induced random capacity reductions into incident management assessment. The theoretical background for the problem is given and a numerical example is provided to illustrate the model's use. Hypothetical scenarios are devised in which the potential IM strategies are assumed to reduce either the average or the variation of the accident duration. For each case, a small scale Monte Carlo simulation is also performed and compared with the analytic results of the stochastic DTA model. It was shown that the stochastic DTA model not only provides the changes in total system travel time within reliability measures, but it also provides the results analytically which requires significantly less computational burden. The stochastic DTA model incorporates the impacts of rerouting which is not possible with queuing theory based analysis on a single link. The results also show that rather than reducing average duration, comparable delay reductions can be achieved by reducing variance while keeping the average accident duration unchanged. This may prove to be an important result as, in general, transportation agencies set targets for maximum accident durations without any considerations on the variance. In other words, policies which may be deemed not to be successful based on its impacts on the average accident duration may in fact be an effective policy to reduce accident delay.

The potential improvements of the model is through the development of a more comprehensive model for accident capacity reduction distribution. For instance, the level of capacity reduction and accident duration are assumed to be independent in the current study. Incorporating the correlation between accident type, the level of capacity reduction and corresponding accident duration can help assess IM strategies from multiple perspectives, i.e. varying IM impacts for different accident types and their corresponding impact on the total system delay.

The accident location and time were also given as an input to the model. Future work will also focus on defining capacity reduction distributions for an arbitrary location and at an arbitrary time. Identification of spatio-temporal capacity distribution (similar to Xie et al., 2015) will allow the evaluation of IM strategies that not only affect accident duration but strategies which aim to reduce accident frequencies.

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