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Original Research Paper

Traffic recovery time estimation under different flow regimes in traffic simulation

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ABSTRACT

Incident occurrence and recovery are critical to the smooth and efficient operations of freeways. Although many studies have been performed on incident detection, clearance, and management, travelers and traffic managers are unable to accurately predict the length of time required for full traffic recovery after an incident occurs. This is because there are no practical studies available to estimate post-incident recovery time. This paper estimates post-incident traffic recovery time along an urban freeway using traffic simulation and compares the simulation results with shockwave theory calculations. The simulation model is calibrated and validated using a freeway segment in Baltimore, MD. The model explores different flow regimes (traffic intensity) and incident duration for different incident severity, and their effects on recovery time. A total of 726 simulations are completed using VISSIM software. Finally, the impact of congestion and incident delay on the highway network is quantified by a regression formula to predict traffic recovery time. The developed regression model predicts post-incident traffic recovery time based on traffic intensity, incident duration, and incident severity (ratio of lanes closure). In addition, three regression models are developed for different flow regimes of near-capacity, moderate, and low-traffic intensity. The model is validated by collected field data on two different urban freeways.

1. Introduction

Freeway congestion is a major problem in many urban areas. Congestion on freeways is classified to recurring and non-recurring. Recurring congestion is from normal peak-hour travel. Non-recurring congestion is from random and unpredictable incidents and events that impede the flow of traffic, such as lane blockage from accidents, disabled vehicles, or natural phenomena. These non-recurring incidents can make large delays that contribute significantly to the total congestion experienced by travelers. Delays are influenced by the nature and frequency of incidents and the traffic intensity before the incident. Accurate estimations of congestion delay

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and its components are important for effective traffic management. Traffic management decisions will be largely influenced by the nature and type of congestion experienced. Traffic management strategies should be emphasized if the accrued delay is largely from recurrent congestion, and the incident management strategies should be applied if the delay is largely incident related (Skabardonis and Geroliminis, 2004).

A literature search is conducted to find past researches related to incident delay estimation and recovery time. The obtained information indicates that most of the available studies utilized the analytical model of queuing analysis (Garib et al., 1997; Giuliano, 1989; Lindley, 1987; Morales, 1986; Olmstead, 1999; Sullivan, 1997) and shockwave analysis theory (Hadi et al., 2007; Knoop, 2010). While these methodologies remain popular, others have concluded that these approaches underestimate the actual queue dissipation time and, ultimately, the full system recovery time (Chien and Chowdhury, 2000; Li et al., 2006). Although these analytical models can reasonably estimate the average delay, they seriously underestimate the standard deviation of delay and the expected total delay in the dynamic traffic networks.

Delay is one of the most important indicators to measure the impacts of incidents. Several methods (queuing and shockwave) are available in the literature for incident-induced delay estimation on freeway networks. The deterministic queuing model (DQM) is one of the most widely used methods and also supported by the Highway Capacity Manual (TRB, 2010).

DQM and shockwave theory are often used to evaluate the characteristics of queue formation and dissipation. DQM is based on assumptions regarding arrival patterns, departure characteristics, and queue disciplines. The queue discipline that most readily assumed for traffic-oriented queues is the first-in, first-out (FIFO).

A shockwave means a discontinuity of flow or density and occurs when cars change speed abruptly. A sudden reduction of the freeway capacity creates backups and queuing, and results in the shockwave effect. The sudden reduction of capacity results from either recurring or non-recurring congestion. The bottleneck results in speed reduction, and the point at which this change occurs can be noted by the brake lights on the vehicles.

According to Skabardonis and Geroliminis (2004), simulation models can be applied to analyze incident impacts without simplifying assumptions which is required by analytical techniques. Furthermore, most previous studies have only estimated the queue dissipation time, and had no standard formulation for full traffic recovery time (TRT) estimation. Therefore, traffic managers in different areas have postulated that post-incident TRT exceeds the actual duration of an incident by a fixed factor. For example, this factor is postulated to be four and ten in Maryland and California, respectively (Chang et al., 2006). While that idea is clearly refutable because the recovery time is a function of the prevailing traffic intensity, it does have some element of truth regarding the relatively longer period of traffic recovery and the actual duration of the incident. In this study, TRT is defined as the time when post-incident traffic flow has returned to pre-incident conditions.

It is usually difficult to accurately predict the length of time required for full traffic recovery after an incident. The probabilistic nature of most non-recurring incidents makes it difficult to collect accurate empirical data to establish a mathematical relationship between incident duration and TRT for different flow regimes or traffic intensity values. The duration of most non-recurring incidents is usually unknown because of one's inability to determine the exact time of occurrence. Microscopic simulation allows for generation of pseudo-incidents for a variety of traffic-flow scenarios. These pseudo-incidents can facilitate a controlled study on the ramifications of delay to highway incident response.

A typical time-density-speed graph of incidents is presented in Fig. 1 to show the difference between queue dissipation and full traffic recovery. The upper line segment in the graph represents the density curve in vehicle per mile (vpm), while the downward slope of the line represents the queue discharge during the traffic stabilization period prior to the onset of full TRT, or pre-incident conditions. The lower line represents the speed curve in miles per hour (mph). The first section is the pre-incident normal condition. The incident begins at T1 and ends at T2. Queue dissipation starts at T2 and ends at T3. Full traffic recovery happens at T4. The time between T1 and T2 is the incident duration when an incident happens, lanes are closed until the incident is cleared and lanes would be re-opened. During the incident, density increases and speed decreases since one or more lanes of the freeway are blocked. After the incident ends, recovery begins and traffic dissipates. Although the queue is dissipated at T3, the traffic is not stabilized. Full incident recovery is achieved when pre-incident conditions are observed, after queue dissipation at T4. The authors considered both speed and density for traffic recovery. Density is a more accurate indicator for traffic congestion along freeways, as freeways can be heavily congested even at free flow speeds.

Computer simulation models have become increasingly important in the analysis, design, and management of transportation/traffic infrastructure and operations. This is particularly true for delay impact, delay analysis, incident detection, and incident management, which form the complex and frequently changing traffic conditions. Since it is expensive and difficult to analyze such situations through empirical methods (due to the large amount of data required), simulation models are often used. In most cases, only limited, if any, field tests are feasible, because of prohibitively high costs and lack

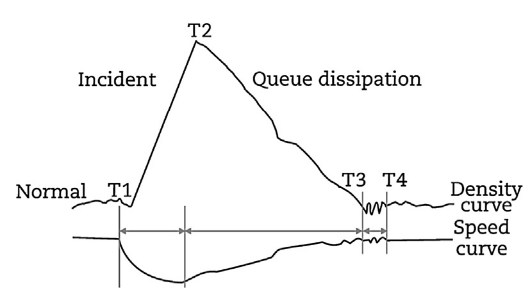

Fig. 1 – Typical time-density-speed graph of incidents and traffic recovery.

of public acceptance (Toledo and Koutsopoulos, 2004). Boyles and Waller (2007) demonstrated that the incident impact is underestimated by 20% to 50%, due to the uncertainty in predicting incident duration. They developed a stochastic delay prediction model to mitigate the underestimation of incident impact. They also employed a mesoscopic simulator with Monte Carlo sampling to study incident delay for different demand profiles. Simulation models also help engineers evaluate alternative transportation strategies and predict outcomes of possible improvements to the transportation systems. The most popular microscopic traffic simulation programs are CORSIM, INTEGRATION, WATSIM, TRANSIMS, MITSIM, PARAMICS, VISSIM, and AIMSUN (TRB, 2010). There are several contributions in the literature on calibration/validation of simulation models to match field conditions (Dowling et al., 2004; Jha et al., 2004; Ni, 2004; Toledo and Koutsopoulos, 2004).

The objective of this study is to present a simulation-based methodology for incident TRT estimation. The present research uses traffic simulation to explore the relationship among incident recovery time, traffic intensity, incident severity, and incident duration, and to compare the simulated data with the result of analytical shockwave traffic recovery estimation model. The relationship is demonstrated using the results from the VISSIM 4.30 traffic simulation model (PTV, 2000). The estimation formula is developed using regression models.

Traffic managers can use the developed formulas to calculate the full TRT based on traffic intensity, incident severity, and incident duration. The research is expected to serve as a valuable guide for incident managers and decision makers as they assess the ramifications of delayed response to highway incidents and develop improved incident-management methods. This research enhances management agencies' ability to quantify the impact of congestion and delay on the freeway network. The improved congestion management also increases the reliability of traffic prediction in advanced transportation information systems and, ultimately, the social welfare of commuters and drivers.

2. Materials and methods

This section discusses the research process and highlights the simulation procedure, determination of the TRT from the simulation outputs, and the shockwave delay calculations.

The authors developed a traffic simulation model to generate traffic intensity and incident duration for different incident severity (lane closure) scenarios. Then, the TRT for each scenario using the developed simulation model was derived. The queue dissipation time (QDT) for each scenario was also calculated using shockwave theory. The results of the models were compared. Finally, the authors developed a regression model using the simulation results to estimate TRT for each lane closure scenario (incident severity), traffic intensity, and incident duration.

2.1. *Traffic simulation*

The authors developed a traffic simulation model for a typical three-lane unidirectional urban freeway. The model generated different incident scenarios of various traffic intensity and duration for different lane closures. Driver behavior parameters were adjusted and included the "look-behind distance" and the "lane-changing" parameters. This eliminated collisions and mini-queues had reduced the overestimation of the queue dissipation time. The VISSIM simulation model was previously calibrated and validated in an earlier study (Saka et al., 2008). A modified Chi-square test known as GEH was employed to validate the model. The calibration and validation was performed on the I-83 freeway corridor known locally as the JFX in Baltimore, MD, by iteratively comparing the model output to the observed traffic performance. Adjustments were made as needed to reasonably replicate the observed condition. Fig. 2 presents the JFX corridor and Table 1 presents a summary of the calibration/validation process, which is based on Oketch and Carrick's criteria (Oketch and Carrick, 2005). Parameters used in the simulator were based on the Wiedemann (1974, 1991) approach or software default values, or obtained by measurement of traffic on the freeway.

Traffic and incident conditions were simulated along a straight and level section of a three-lane unidirectional freeway for at least 150 min (the software's maximum allowed simulation time). Different scenarios of incident durations and traffic intensity levels (Rho values) were generated. The Rho is a measure of traffic intensity along a segment of the freeway and is defined by the volume-to-capacity ratio (V/C). Freeway capacity was determined as 2400 vehicles per hour per lane (vphpl). Freeway capacity was defined as the traffic volume at which the throughput did not change or declines even as the input flow continually increased. For basic freeway segments with no incidents, Highway Capacity Manual (TRB, 2010) recommends an ideal capacity of 2250–2400 vphpl depending on free flow speed.

Traffic intensity was categorized into three levels, light (0.25 ≤ Rho ≤ 0.50), moderate (0.50 < Rho ≤ 0.80) and near capacity (0.80 < Rho < 1.00). Then, incidents of various

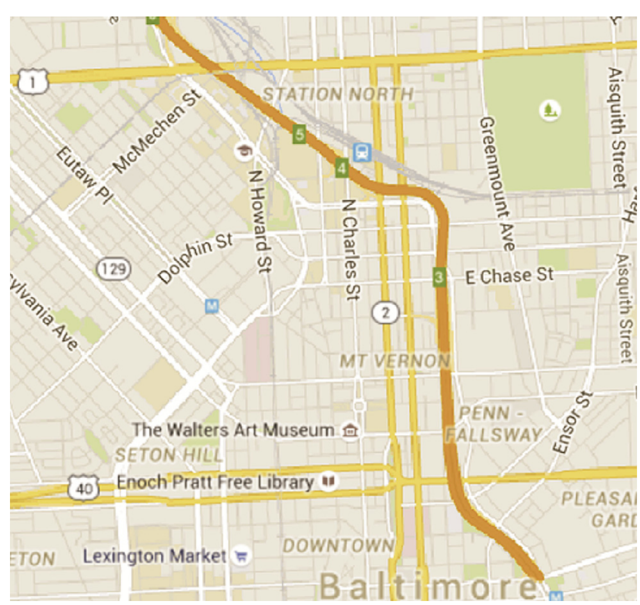

Fig. 2 – JFX corridor.

Table 1 – Observed versus simulated throughputs in study area.

JFX segment southbound	Observed volume o (vph)	Simulated volume range e (vph)	GEH $\left(\sqrt{\frac{(o-e)^2}{0.5(o+e)}}\right)$	Validation criteria (GEH < 5) met?
Between Exit 5 and Exit 4	8075	7595–7879	2.20	Yes
Between Exit 4 and Exit 3	7120	7434–7731	3.68	Yes
Between Exit 3 and Exit 2	5886	5979–6184	1.21	Yes
Between Exit 2 and Exit 1	5712	5141–5497	2.87	Yes
Southbound right onto Fayette Street	1429	1284–1428	0.00	Yes
Southbound through onto President Street	2673	2097–2336	6.73	No*
Southbound left onto Fayette Street	1610	1392–1592	0.45	Yes

Note: * A GEH between 5 and 10 is not considered to indicate that the model is a poor fit, but does indicate that further investigation is required.

durations were generated for these traffic demand levels. Incident durations were defined as short (inc ≤ 20 min), moderate (20 min < inc ≤ 40 min) and long (40 min < inc ≤ 60 min). The timed incidents were preceded by a 30-min traffic build-up along the simulated freeway segment. The experiments covered various lane-blockage scenarios for the three-lane freeway segment. Since VISSIM cannot simulate road incidents directly, the authors created pseudo-incidents using traffic signals. In addition, only one isolated incident per time and space were considered in the simulation. In other words, the impacts of multiple incidents on congestion and recovery time were not included in the scenarios.

A total of 121 scenarios of Rho and incident duration were generated, each with six random seeds, therefore, a total of 726 (121 × 6) experiments were simulated. Of the 121 scenarios, 97 scenarios involved 3 blocked lanes, 12 scenarios involved 2 blocked lanes, and 12 scenarios involved 1 blocked lane. From these 726 experiments, output values for flow, density, speed, and TRT values were derived. Various lane-blockages indicate incident severity, with more lanes closed, the incident would be more severe.

The effective Rho value for each scenario was derived as a ratio of total traffic demand for the simulation period to effective capacity for the specified incident duration. Total traffic demand was calculated for the simulation period at the specified traffic intensity or initial Rho value. Effective capacity was defined as the potential throughput for the simulation period less than the unmet demand for the incident duration at the specified traffic intensity level or original Rho value.

2.2. *Determination of simulation values for TRT*

Determination of the post-incident TRT was based on the pre-incident traffic conditions of density and speed.

The authors determined TRT when post-incident density values were the same as pre-incident values. Although speed values were also considered, density values were a more accurate indicator of traffic congestion along freeways, as freeways can be heavily congested even at free flow speeds. A t-test was then conducted to investigate if there were any significant differences between the pre- and post-incident density values. The t-test results presented in Table 2 verify that there is no significant difference, which means that the TRT is determined correctly in all scenarios.

2.3. *Queue dissipation time calculations using shockwave theory*

The authors calculated the queue dissipation time for each three-lane-closed scenario using the following formulas

$$u_1 = \frac{q_2 - q_1}{k_2 - k_1} = \frac{0 - q_1}{k_j - k_1} \tag{1}$$

$$u_2 = \frac{q_3 - q_2}{k_3 - k_2} = \frac{q_{\max} - 0}{k_c - k_j} \tag{2}$$

$$u_3 = \frac{q_4 - q_1}{k_4 - k_1} = \frac{q_{\max} - q_1}{k_c - k_1} \tag{3}$$

$$Q = t_1 u_1 \tag{4}$$

$$t_2 = \frac{Q}{u_2 - u_1} \tag{5}$$

where u_1 is queue build up rate (mile/h), u_2 is queue dissipation rate (mile/h), u_3 is normal stabilization flow rate (mile/h), q_1 is pre-incident flow rate (veh/h), q_2 is incident flow rate (veh/h), q_3 is capacity flow rate (veh/h), q_4 is stabilization flow rate (veh/h), $q_{\max}$ is maximum flow capacity (veh/h), k_1 is pre-incident density (veh/mile), k_j is jam (incident) density (veh/

Table 2 – Summary results of *t*-test for paired two samples (density means).

Traffic intensity (Rho)	Incident duration (min)	Pre-incident density means	Post-incident density means	Sample size N	t-stat	P-value	t critical
0.9	10	116	117	6	−0.227	0.829	2.571
0.8	15	103	103	6	0.095	0.928	2.571
0.8	30	106	102	4	1.367	0.265	3.182
0.7	50	91	88	3	1.389	0.299	2.571

mile), k_c is capacity (dissipation) density (veh/mile), Q is queue length (mile), t_1 is incident duration (h), t_2 is queue dissipation time (h).

When comparing simulation and shockwave, the authors considered only the case that all lanes of the freeway were closed, $q_2 = 0$. This was done in order to evaluate the worst-case scenarios for TRT of all lanes closed. Further, the authors used simulation values for k_j, k_c, and q_{max} instead of actual field data because of two reasons. First, this would be feasible to compare the results of the shockwave theory calculations with the simulation results. Second, it would be very time-consuming and expensive to collect all scenarios of incident duration and traffic intensity. Since only non-recurring incidents were considered, it would be even more difficult to collect the actual field data.

Previous literature suggests shockwave theory calculates only queue dissipation time, which is different from TRT. In order to make a fair comparison of the simulation results and shockwave theory calculations, the authors proposed a formula to calculate the full TRT for shockwave with both the summation of queue dissipation time and the stabilization time as follows

$$t_4 = t_2 + t_3 \tag{6}$$

$$t_3 = \frac{Q}{u_3} \tag{7}$$

where t_3 is shockwave stabilization time, t_4 is shockwave recovery time.

As stated earlier, full TRT is defined as the time after incident clearance when pre-incident traffic flow conditions resume. Therefore, the full TRT is the summation of queue dissipation time and traffic stabilization time. The authors defined the queue stabilization time as the queue length divided by the stabilization rate.

3. Results and discussion

This section presents the outputs of the simulation scenarios and a statistical analysis of TRT for different incident and traffic demand regimes. Results of the shockwave calculations for TRT and a comparison of methods (simulation vs. shockwave) are also presented.

3.1. *TRT from simulation*

Presented in Table 3 are the aggregated results for 3 lanes blocked, 97 cases, each with 6 random seeds (582 experiments) of derived TRT for different scenarios of Rho and incident durations. Results for 13 of those scenarios were omitted from further analysis because the normal pre-incident condition was not attained within the 150-min simulation period.

The recovery time values derived from traffic simulations ranged from a high value of 97 min to a low value of 9 min, depending on the demand or traffic intensity levels and incident duration. For example, a 60-min recovery time is associated with scenarios for NC–SI, MT–MI, and LT–LI. Scenarios for Rho 0.90 and 5 min incident, Rho 0.60 and 35 min incident, and Rho 0.50 and 60 min incident all have a recovery time of almost 60 min.

Fig. 3 presents typical density profiles for the same incident duration as traffic demand increases. As expected, the graph confirms that within the same incident duration, TRT increases nonlinearly as traffic intensity builds. Further analysis of the results suggests that as traffic intensity approaches the capacity threshold (Rho equals 1), recovery time becomes indefinite. Consequently, congestion increases as incident duration increases at all Rho (demand) values. Similarly, density profiles for different incident duration and increasing traffic intensity levels confirm that a lower incident time does not necessarily result in a lower recovery time, as TRT is a function of both incident duration and traffic intensity. Only if traffic demand is fixed the lower TRT with the lower incident time. Fig. 4 shows a 3-dimensional view of the variability level in TRT associated with varying incident durations and traffic demands.

3.2. *Comparison between shockwave and simulation*

TRT was also calculated by shockwave theory for the same scenarios of traffic intensity and incident duration. Table 4 presents the parameters used to calculate shockwave TRT.

Table 3 – Estimated TRT from traffic simulation.

Incident duration (min)			Short (SI) (inc ≤ 20)				Moderate (MI) (20 < inc ≤ 40)				Long (LI) (40 < inc ≤ 60)			
Lane closure	Traffic intensity (Rho)		5	10	15	20	25	30	35	40	45	50	55	60
3-lane blocked	Near capacity (NC) (0.80 < Rho < 1.00)	0.95	76											
		0.90	59	84	88									
		0.85	35	58	78	90	93							
	Moderate traffic (MT) (0.50 < Rho ≤ 0.80)	0.80	28	47	60	77	89	94	97					
		0.75	21	35	51	62	73	74	81	X	X			
		0.70	21	34	49	57	62	72	77	X	X	X	X	X
		0.65	16	26	35	43	51	64	68	71	73	X	X	X
		0.60	15	21	28	36	43	51	60	67	69	X	X	X
	Light traffic (LT) (0.25 ≤ Rho ≤ 0.50)	0.50	15	19	24	29	35	38	42	46	50	55	58	60
		0.35	12	14	15	21	23	27	28	30	32	35	38	40
		0.25	9	11	12	15	16	17	18	20	21	23	25	26

Note: X is post-incident TRT values omitted, as normal pre-incident condition is not attained during the 150 min simulation period.

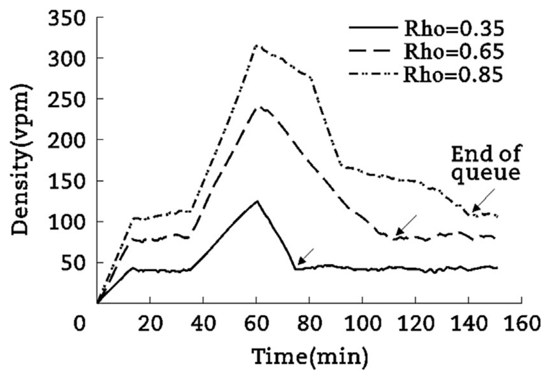

Fig. 3 – Simulation results of 25-min incident duration for varying demand levels.

Table 4 – Parameters used in shockwave calculations.

Parameter	Value
k_j (veh/mile)	263
k_c (veh/mile)	132
q_{max} (veh/h)	7200

Table 5 presents a sample of the results and compares the estimated TRT values from simulation and from shockwave theory. In all cases, the simulated TRT values exceed the recovery time derived from shockwave methodology. On the other hand, the shockwave model's queue dissipation time is almost half of the value which was observed in the simulation.

The shockwave model calculations indicate that shockwave TRT approximates simulated TRT for LT–LI, MT–MI, and MT–LI scenarios. For short incidents with both off-peak (light traffic) and peak (near capacity) demand levels, TRT for almost all (except 2) cases differs by more than a 2:1 ratio for simulation values versus shockwave results.

When traffic intensity is moderate or near capacity, shockwave TRT exceeds incident duration. When traffic is light, TRT is less than incident duration. The simulation values also show varying ratios of incident to TRT depending on the variation of traffic demand. Preliminary analysis shows that the ratio of incident duration to TRT varies and when traffic demand is at low traffic (Rho < 0.60) within moderate to long incident durations, TRT is approximately a factor of one. At moderate traffic with short incident duration, the factor of incident duration to TRT varies from 2 to 6. The variation in recovery time cannot be adequately described by one consistent ratio but is, in fact, determined to a certain extent based on the traffic demand at the time of the incident. As presented in Table 5, this ratio is between 1 and 15.

As stated earlier, the shockwave formula to calculate TRT was developed only for all 3 lanes closed. When only one or two lanes are closed, q_2 is not zero and vehicles merge to other lanes. Too many assumptions need to be made to develop an accurate TRT formula. The authors decided to compare only all lanes closed in order to show the differences between results from simulation and shockwave models, which could demonstrate the superiority of simulation method.

Low traffic intensity and variations of incident duration resulted in little or no change in the TRT for partial-lane-blockage scenarios. Consequently, fewer scenarios (12 scenarios) were analyzed for the 3-lane-blocked scenarios. The recovery time incrementally increased as the number of lane closures increased from one to three lanes. Table 6 compares TRT values for different lane-blockage scenarios.

3.3. *Regression results*

Regression analysis was employed to formulate the TRT based on traffic intensity, incident duration, and incident severity.

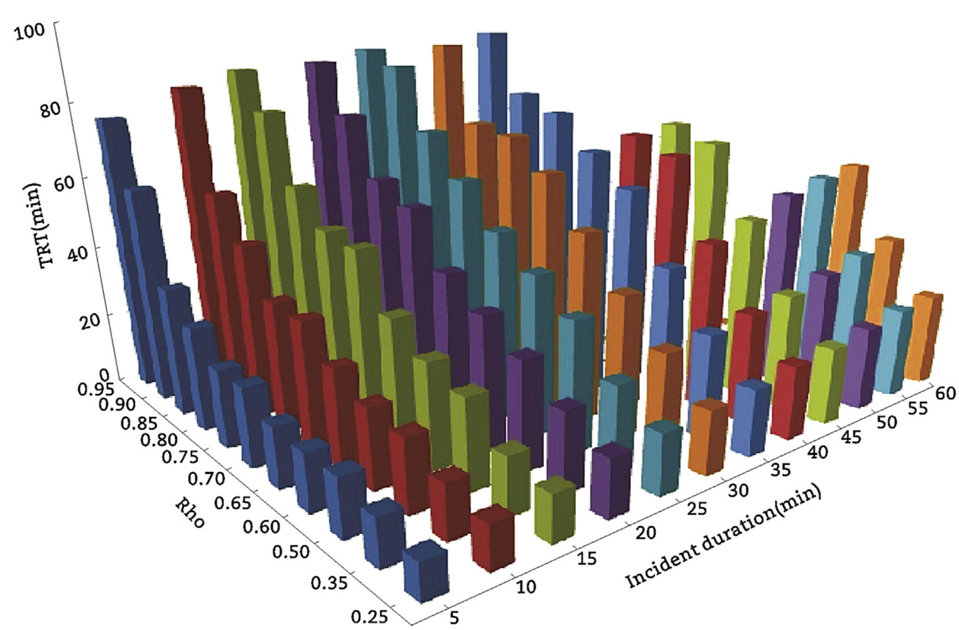

Fig. 4 – TRT versus Rho and incident duration.

Table 5 – Comparison of TRT values from simulation and shockwave models (based on scenario matrix).

Scenario matrix	Incident duration t_1 (min)	Original Rho	Simulation dissipation time (min)	Shockwave dissipation time (min)	Shockwave recovery time t_4 (min)	Simulated recovery time t_5 (min)	t_5/t_4	t_5/t_1
LT–LI	45	0.50	39	21	37	50	1.3	1
LT–LI	55	0.35	32	14	26	38	1.4	1
LT–LI	60	0.25	23	10	19	26	1.4	0
LT–LI	60	0.50	48	28	50	60	1.2	1
LT–MI	25	0.25	11	4	8	16	2.1	1
LT–MI	30	0.35	18	8	14	27	1.9	1
LT–MI	35	0.50	33	16	29	42	1.5	1
LT–SI	5	0.35	4	1	2	12	4.9	2
LT–SI	5	0.25	2	1	2	9	5.9	2
LT–SI	5	0.50	6	2	4	15	3.5	3
LT–SI	10	0.25	5	2	3	11	3.4	1
LT–SI	10	0.35	7	3	5	14	3.0	1
LT–SI	15	0.50	18	7	12	24	2.0	2
LT–SI	15	0.25	7	2	5	12	2.6	1
LT–SI	20	0.25	9	3	6	15	2.5	1
MT–LI	45	0.60	61	30	53	69	1.3	2
MT–LI	45	0.65	61	36	62	73	1.2	2
MT–MI	25	0.60	44	17	29	43	1.5	2
MT–MI	25	0.75	55	30	51	73	1.4	3
MT–MI	30	0.65	41	24	42	64	1.5	2
MT–MI	30	0.75	56	36	61	74	1.2	2
MT–MI	35	0.70	64	34	58	77	1.3	2
MT–MI	35	0.80	64	53	88	97	1.1	3
MT–SI	5	0.70	14	5	8	21	2.6	4
MT–SI	5	0.80	15	8	13	28	2.2	6
MT–SI	10	0.60	18	7	12	21	1.8	2
MT–SI	15	0.70	35	15	25	49	1.9	3
MT–SI	15	0.80	66	23	38	60	1.6	4
MT–SI	20	0.65	28	16	28	43	1.6	2
MT–SI	20	0.75	53	24	40	62	1.5	3
NC–MI	25	0.85	79	49	80	93	1.2	4
NC–SI	5	0.85	25	10	16	35	2.2	7
NC–SI	5	0.90	37	13	22	59	2.7	12
NC–SI	5	0.95	45	19	35	76	2.2	15
NC–SI	15	0.90	81	39	66	88	1.3	6
NC–SI	20	0.85	47	39	64	90	1.4	5

Statistical analysis of the simulation results indicates that TRT is exponential and its natural logarithm transformation can be reasonably represented as a linear function of incident duration and traffic intensity. However, the authors found that when scenario is defined within the specified ranges of traffic intensity level, a better model is obtained using a regression model to estimate the coefficients of this relationship.

Four different regression models were explored, aggregated for all scenarios, based on traffic intensity levels as defined above, and for each lane blockage scenario separately. The developed regression model is as follow, and the results are presented in Table 7.

$$\ln(\mathrm{TRT}) = \alpha + \beta t_1 + \gamma Rho + \theta L \tag{8}$$

where L is the ratio of lanes closed, α is a constant, β, γ, θ are coefficients.

All regression models with 0 intercept show a strong correlation among all the variables, with high adjusted R^2 values. It suggests that over 85% of the variance in post-incident traffic recovery can be explained by the variables of traffic intensity, incident duration, and the proportion of lane closure. Note that "L" in the regression formula is the proportion of lane closed, e.g., when one lane out of the three lanes of the freeway is closed, L is 1/3 or 0.333.

3.4. *Model validation*

The developed simulation-based regression model was validated using real-world data. The authors obtained incident data from the Regional Integrated Transportation Information System (RITIS) in CATT Laboratory at the University of Maryland, College Park (RITIS, 2012). RITIS integrates existing transit and transportation management data from different sources. The main RITIS functions are the real-time fusion and exchange of regional transportation data, and data archiving. The major data sources are traffic cameras. The authors extracted traffic data for incidents on I-83 and I-695 that occurred from June to September, 2011, based on the cameras located on these two urban freeways. Number of lanes closure, incident duration, and Rho were extracted from the database and TRT was derived based on the

Table 6 – Sample results comparing TRT values for different lane closure scenarios.

Simulation scenario		TRT (min)		
Incident duration (min)	Original Rho	3-lane Closure	2-lane Closure	1-lane Closure
10	0.90	86	57	28
15	0.90	93	74	42
15	0.85	78	52	26
15	0.80	60	44	17
15	0.75	51	35	16
15	0.70	49	31	11
30	0.80	85	62	22
30	0.75	71	54	19
45	0.75	72	68	33
50	0.70	65	60	26
55	0.65	64	53	30
60	0.70	*	60	32

Note: * Post-incident TRT was omitted because it was inconclusive.

database speed information in the same way it was calculated for simulation results. TRT was also predicted using the developed regression formulas as presented in Table 8. The authors compared the predicted TRT using regression analysis with the observed ones. The authors excluded row 19 in Table 8 since it did not seem to be realistic to have a 10-min observed TRT when the traffic was almost at capacity (Rho = 0.99) and the incident duration was 41 min. It could be a data collection error. Columns in Table 8 present Rho, proportion of the lanes closure, incident duration, observed TRT, and predicted TRT.

The authors conducted a single regression between observed and predicted TRT. The regression results indicate that the predicted TRT using the regression model developed by the authors explains 82% of the observed data ($R^2 = 0.821$) as presented in Table 9. The authors also used a Wilcoxon rank-sum test, which was a non-parametric test, to compare the observed and predicted TRT values. The test results showed no significant difference between the probability distributions of the predicted and the observed TRT with 95% confidence level ($Z = -2.451$, Sig. = 0.014).

Based on the Wilcoxon test and regression results, the authors' simulation-based regression model provides a reliable formula to predict TRT for different flow regimes on urban freeways. The model can be utilized for urban freeways other than I-83, within the defined clonstraints, since I-695's predicted TRT was close to the observed TRT.

4. Conclusions

This study proposed a methodology for estimating post-incident traffic recovery time (TRT). Traffic simulation was utilized to evaluate how different combinations of demand (V/C), incident duration, and incident severity (lane closure proportion) affected incident recovery time. Simulation was utilized to have all different combinations of traffic demand (or intensity, V/C of 0.1–1.0), incident duration (5–60 min), and incident severity (the proportion of lanes closure). A total of 726 simulations were completed. Finding all these combinations was almost impossible from real-world data.

The authors then applied the simulation output results for speed, density, and flow to well-known analytic delay prediction formulas to compare the results of TRT. In addition, the authors developed a regression model that can reasonably estimate recovery time based on 3 primary variables: traffic intensity, incident duration, and lane closure proportion. TRT is defined as the period elapsing after incident clearance when traffic returns to pre-incident conditions.

Since full TRT estimation has not been widely explored in literature, this research is relevant and timely to the transportation industry and the transportation management center (TMC) responsible for smooth and efficient freeway and highway operations. Most traffic managers have postulated that the post-incident TRT exceeded the actual incident duration by a fixed factor.

The traffic simulation results indicate that congestion increases as incident duration increases at all demand levels but increases at faster rates for higher traffic demand. However, recovery time becomes indefinite as traffic intensity approaches capacity threshold. This suggests that TMCs should implement alternate incident management strategies once a certain demand threshold is reached. A regression model was developed to estimate TRT using the simulation results. The regression model was applied to different combinations of traffic intensity level, incident durations, and lane blockage. All regression models show a very strong positive relationship between a natural log of TRT and incident time, demand, and incident severity. The validity of the simulation-based regression model results was successfully tested using the collected field data.

Table 7 – Regression results for aggregated, traffic intensity, and lane blockage scenarios.

Regression model		α	β	γ	θ	R^2	Adj. R^2	N
All scenarios aggregated		−0.406 (0.1705)	0.0216 (8.18E−13)	2.634 (1.49E−22)*	1.833 (2.01E−13)	0.662	0.653	121
Traffic intensity level	Near capacity	−0.382 (0.784)	0.024 (0.0001)	3.179 (0.051)	1.188 (0.009)	0.480	0.443	47
	Moderate traffic	−1.766 (0.016)	0.025 (7.58E−08)	3.679 (8.98E−05)	2.392 (2.81E−10)	0.676	0.655	50
	Low traffic	1.512 (5.94E−12)	0.016 (6.77E−12)	3.113 (1.01E−08)	–	0.942	0.882	24

Note: * The numbers in parenthesis are *P*-values of coefficients. *P*-values less than 0.05 are considered significant at the 95% level of confidence interval.

Table 8 – Comparison of observed and predicted TRT values.

Case	Rho	Lane closure proportion	Incident duration (min)	RITIS observed TRT (min)	Predicted TRT (min)
1	0.53	0.67	10.00	15.00	14.81
2	0.18	0.33	109.00	21.00	26.83
3	0.46	0.33	30.00	45.00	11.28
4	0.18	0.00	22.00	3.00	2.61
5	0.09	1.00	72.00	20.00	25.43
6	0.31	0.67	20.00	13.00	9.72
7	0.30	1.00	23.00	22.00	16.38
8	0.50	0.33	37.00	18.00	14.72
9	0.36	0.67	31.00	59.00	14.25
10	0.30	1.00	21.00	15.00	15.92
11	0.14	0.33	33.00	22.00	4.85
12	0.57	0.33	26.00	20.00	13.98
13	0.58	0.67	18.00	17.00	20.04
14	0.94	0.33	44.00	51.00	58.02
15	0.40	0.67	14.00	21.00	11.00
16	0.56	0.33	15.00	37.00	10.80
17	1.02	0.33	4.00	45.00	31.20
18	0.67	1.00	19.00	69.00	43.32
19	0.99	0.67	41.00	10.00	103.44
20	0.66	0.67	30.00	45.00	31.82
21	0.68	0.33	53.00	48.00	33.92
22	0.70	0.33	30.00	25.00	22.30
23	0.92	0.33	16.00	24.00	30.23
24	0.30	0.00	4.00	3.00	2.55
25	0.31	1.00	24.00	34.00	17.36
26	0.47	0.67	72.00	45.00	46.25
27	0.55	0.33	51.00	11.00	22.54
28	0.66	0.67	20.00	24.00	26.49
29	0.33	0.00	1.00	2.00	2.57
30	0.51	1.00	36.00	38.00	39.45
31	0.61	0.33	15.00	18.00	12.41

Comparative analysis of the simulation- and shockwave-derived TRT values suggests that the simulation model offers some advantages over the traditional shockwave model. Except for the low traffic (off-peak) scenarios, the simulation-based TRT estimates consistently exceeded the shockwave-derived estimates. In those low traffic scenarios, the shockwave-derived TRT approximated the simulation-derived results. The shockwave-derived results were consistently lower for both queue dissipation and recovery time.

Engineers and safety officials can apply the developed formulas within the defined constraints to estimate the TRT after an incident along an urban freeway instead of using a fixed factor, such as 4. The simulation model is a better alternative because it can model various incident durations and scenarios.

The ability to utilize extensive simulation data in scenario analysis will enhance the management agencies' ability to quantify the impact of congestion and delay on the highway network. The regression formula for determining post-incident TRT will enable traffic management personnel to systematically ascertain the magnitude of traffic congestion conditions along highways. In addition, it will be possible to reasonably estimate the effect of proportional lane closures and increase traffic intensity on congestion buildup.

The authors considered only three factors, traffic intensity, incident severity, and incident duration that affect TRT. While other factors such as road geometry could affect TRT, the authors tried to develop a very simplistic method to be usable by practitioners. An extension to this model could add more factors and also account for the rubbernecking effect. Another extension to this study would consider the impact of multiple incidents on congestion and recovery time.

Table 9 – Regression results for observed TRT versus predicted TRT.

Regression	Predicted TRT	R^2	Adj. R^2	N	P-value
Coefficient	1.17	0.821	0.786	30	2.30E−12

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