DESIGN OF AN EFFICIENT EMERGENCY RESPONSE SYSTEM TO MINIMIZE THE INCIDENT IMPACTS ON HIGHWAY NETWORKS: A CASE STUDY FOR THE MARYLAND DISTRICT 7 NETWORK

Hyeonmi Kim
Department of Civil Engineering
1173 G. Martin Hall, Dept. of CEE,
University of Maryland at College Park
College Park, MD 20740 USA
(301) 405-2638, (301) 405-2585, hmkim@umd.edu

Woon Kim*
Department of Civil Engineering
1173 G. Martin Hall, Dept. of CEE,
University of Maryland at College Park
College Park, MD 20740 USA
(301) 405-6959, (301) 405-2585, wkim2@umd.edu

Gang-Len Chang
Department of Civil Engineering
1173 G. Martin Hall, Dept. of CEE,
University of Maryland at College Park
College Park, MD 20740 USA
(301) 405-1953, (301) 405-2585, gang@umd.edu

Steve M. Rochon
Division Chief
Traffic Development and Support Division
Office of Traffic and Safety
Maryland State Highway Administration
7491 Connelley Drive
Hanover, MD 21076 USA
(410) 787-5860, srochon@sha.state.md.us

* Corresponding author

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DESIGN OF AN EFFICIENT EMERGENCY RESPONSE SYSTEM TO MINIMIZE THE INCIDENT IMPACTS ON HIGHWAY NETWORKS: A CASE STUDY FOR MARYLAND DISTRICT 7 NETWORK

ABSTRACT

Analysis of incident data from Maryland Highway Administration leads to the conclusion that efficient operations of an incident management team can indeed contribute to reduction in not only the response time but also the clearance time. Hence, this paper presents an integer-programming model for optimizing the deployment locations of emergency response units. Unlike most existing studies, the proposed model is designed to assign the available units to minimize the total delay caused by incidents, rather than to minimize their average response times. By giving more weights to locations likely to have more severe incidents and considering the variance of incident duration, the proposed model with the incident data from Maryland can outperform both the popular *p*-median model and state-of-the-practice deployment strategies. Extensive sensitivity analyses with respect to various traffic volumes and incident frequencies have also confirmed the superior performance of the proposed model with respect to minimizing the total delay caused by incidents.

1. INTRODUCTION

Various studies (*1–3*) have pointed out that traffic incidents, including disabled vehicles, fire, road debris, constructions, police activities, and vehicle crashes, have long been recognized as the major congestion contributor and a significant threat to urban mobility as well as safety. For instance, FHWA (*1*) reported that incidents caused about 25 percent of congestion in the U.S.A. Thus, many transportation agencies over the past decades have implemented various freeway incident management systems to reduce the incident impacts on highway networks.

One of the key issues associated with efficient incident management is how to locate/allocate the available resources in response to the temporal and spatial distributions of incidents. Most existing studies on this subject can be divided into two categories – patrolling and dispatching strategies. In recent years, many transportation agencies have introduced patrol-based response programs due to their relative effectiveness in detecting incidents and convenience of operations (*3–7*). For example, Lou et al. (*8*) developed a strategy for the freeway service patrol (FSP) program by considering the involvement of commercial towing services. However, some researchers (*9, 10*) claimed that it is more efficient to strategically deploy response units and dispatch them to the target sites after the incidents being detected. Hence, this study intends to focus on the dispatching rather than patrolling strategies with the objective of minimizing the total delay incurred by incidents.

In review of the incident response literature, it is noticeable that many dispatching strategies have been introduced mainly to minimize the number of service stations, the total operational costs, or to maximize the demand (incidents) covered by the pre-determined number of facilities. Otherwise, they rather focus on minimizing the number of response units required to cover the target area with a predefined level of service, or maximizing the demand that can be covered by available emergency units (i.e., Maximal Coverage Location Problem (MCLP)).

However, most of the aforementioned studies are not directly applicable to address the highway incident response issue as the primary goal of such systems is to minimize incident impacts by reducing incident durations, including response and clearance times. Several studies in the literature (*11, 12*) reported that prompt incident response can decrease not only the response times but also the clearance times, which will result in reducing the total incident-induced delay. Therefore, this study first uses CHART, an incident response system by MSHA, to show the contributions of such systems on reducing incident duration, and then, presents an optimal deployment strategy for available response units to further improve the system's effectiveness. Unlike previous studies, mostly aiming to reduce the average response time, the proposed model is focused on total delay minimization. With such a new objective function, the proposed model has demonstrated its effectiveness over those with the convention methods of minimizing the average response time.

2. LITERUTURE REVIEW

The issue of deploying emergency service units shares some common concerns with those for facility location assignment (13), especially on the following two key decisions: how many response units are needed, and where should they be allocated in response to the temporal and spatial distribution of incidents. In view of a large body of existing studies, including both stochastic and deterministic models, on this subject, this paper will review mainly those related to roadway emergency response or highway incident operations. More specifically, this section will focus on summarizing related literature on the following categories: covering models, *P*-center models, and *P*-median models.

Covering Models

Covering models are the most widely used approach which attempts to provide coverage to all demands within a pre-determined distance range. The earlier version of this model is the location set covering problem (LSCP) introduced by Toregas et al. (14). It seeks to identify the minimum number of facility locations required to cover all demand points. This model has been evolved to various forms of the maximal covering location problem (MCLP) by numerous researchers (15-18) with the objective of maximizing the coverage of demands subjected to resource constraints and the minimal service levels.

These models have also been extended to take the stochastic nature of emergency events into accounts in various ways (19, 20). For instance, ReVelle and Hogan (21) proposed the probabilistic location set covering problem (PLSCP) to place facilities to maximize the probability of service units being free to serve within a particular distance by using an average server busy faction (q_i) and a service reliability factor (a) for demands. Their model has been further modified and enhanced by many researchers (22-27).

Along the same line, Schilling (28) has incorporated individual scenarios to identify a range of good decisions for locations and then to determine the final locations which are a compromise decision to all scenarios. Nair and Miller-Hooks (29) have solved a probabilistic and integer program model by adapting the multi-objective model proposed by Sathe and Miller-Hooks (30). Their model determined the optimal locations/relocations for EMS (emergency medical services) units to maximize double coverage (more robust solutions that each demand node can be covered by two facilities (21)) while minimizing the fixed and relocation costs. Some other stochastic approaches are available in the literature, including stochastic programming (SP) and robust optimization (RO) (31).

P-center models

The *P*-center model assumes that a demand is to be served by the nearest facility, thus making full coverage for all demand points always possible by minimizing the maximum distance between any demand and its nearest facility. The first *P*-center model (32) has attempted to identify the center of a circle with the smallest radius that can cover all target destinations. One of the variations since then has been conducted by ReVelle and Hogan (33). They sought to minimize the maximum distance for available EMS units with the specified service reliability (α) for all demands.

For the same issue, Hochbaum and Pathria (34) tried to minimize the maximum distances on the network which vary over times. Another application has been conducted by Talwar (35) to locate and dispatch three rescue helicopters for EMS demands in order to minimize the worst response time. In addition to those models, a wide range of similar applications is available in the literature (36-40).

P-median models

In general, the accessibility and effectiveness of facilities increase as the average/total distance decreases. Using this property, Hakimi (10) introduced the *P*-median method to locate *P* facilities in order to minimize the average (or total) distance between facilities and demands. Several variants related to their work have been later proposed in the literature, which include modeling the formulations as a linear integer program (41), producing a dynamic strategy (42), and adopting priority dispatching for EMS system which consists of advanced life support (ALS) units and basic life support (BLS) units (43).

Variations of the *P*-median model by accounting for stochastic natures have also been proposed by several researchers. For example, Mirchandani (44) incorporated the uncertainty associated with the availability of service units into the model, whereas Serra and Marianov (45) introduced the concept of "regret" to search for a compromise solution by minimizing the maximum regret over the identified scenarios which are described by various uncertain factors.

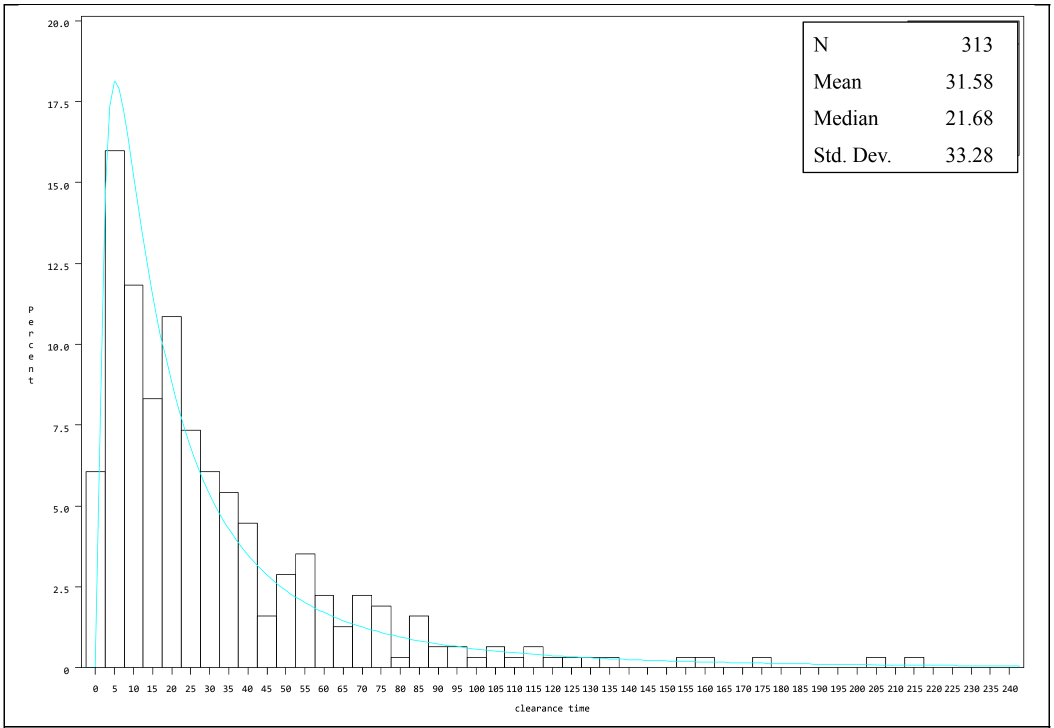
Haghani et al. (46) took the concept of priorities into accounts in their model which is to integrate with a dynamic shortest path algorithm. They categorized their demands (incidents) into five priorities based on severity, and applied them to the objective function to minimize the total weighted travel time. By assigning higher weights to higher priorities, their model intends to respond to severe incidents faster. In addition, the proposed model was integrated with a dynamic shortest path algorithm, based on the real-time traffic information to avoid congested routes and to reallocate units to more promptly respond to severe incidents. This model has been extended to optimize depot locations and the fleet size at each depot (47). It has also been enhanced to relocate depots for remaining vehicles (when several units are on duty) so as to maximize the coverage area (48).

Note that the above brief review covers only some examples of such studies which have been considered by state highway agencies in real-world operations. The remaining part of this paper will first show the effectiveness of the incident response system by Maryland State Highway Administration (MDSHA) with its experienced-based strategy, and then present our proposed model and evaluate its effectiveness with the same incident data.

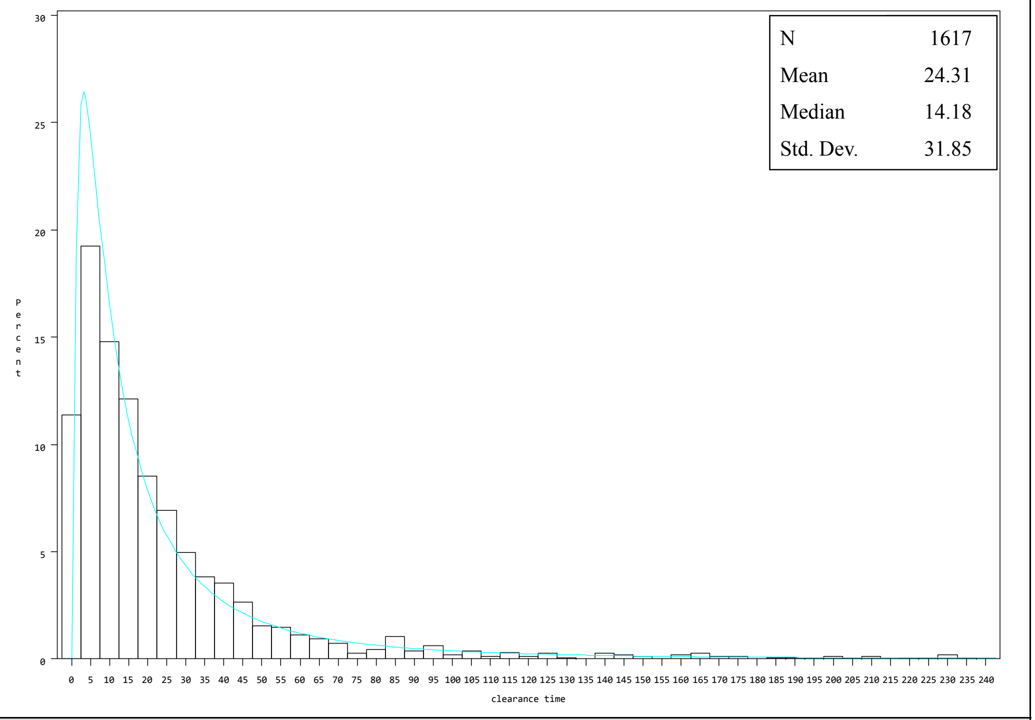
3. EFFECTS OF AN INCIDENT MANAGEMENT PROGRAM ON INCIDENT DURATION

To justify the use of minimizing total incident-induced delay as the objective function in design of an incident response system, one needs to first explore the relation between response efficiency and incident duration. MDSHA has operated an incident traffic management program, named Coordinated Highway Action Response Team (CHART), to minimize the impacts of incidents on highway networks by prompt response, efficient clearance, and effective traffic management. Their major tasks at incident sites include setting up traffic control devices, directing traffic flows, and assisting the fire department, police, or other related agencies to expedite incident clearance operations.

Over the past two decades, CHART has documented incident related information, such as time, locations, nature, involved vehicles, lane closure status, etc., to its database (CHART II Database), and provided analysis results for enhancing the field operations. Figure 1 shows the clearance time distributions based on incidents data from the 2012 CHART II Database. The entire dataset includes two groups of incidents: one that CHART did not respond to (*Type 1*) and the other managed by CHART (*Type2*). Both Type 1 and Type 2 distributions are highly skewed toward right, but the clearance times in *Type 2* concentrate on the range shorter than those in *Type 1*. The average clearance times for *Type 1* and *Type 2* are 31.58 minutes and 24.31 minutes, respectively. The *t*-test results reject the null hypothesis that those average clearance times are equal at the 95 percent significant level. Such statistical results confirm that clearance times of those incidents responded by CHART are shorter than those managed by other agencies.



Without CHART involvement (*Type 1*)



With CHART involvement (*Type 2*)

Note: 1. Data include incidents occurring during a.m. peak hours (7 a.m. – 9:30 a.m. on weekdays) in Maryland in 2012

2. The analysis only includes clearance times between 1 minute and 4 hours.

FIGURE 1 Clearance Time (minutes) Distributions by CHART involvement

To further confirm the findings, this study has divided the incidents responded by

CHART into two groups, where *Type 2-1* refers to those first responded by CHART and *Type 2-2* denotes those incidents first managed by other agencies and then followed by CHART. Figure 2 presents the distribution of clearance times of each group, where both are also highly skewed toward right. But the clearance times of incidents first responded by CHART concentrate more on a range shorter than those first responded by other agencies. The average clearance times for *Type 2-1* and *Type 2-2* are 20.54 minutes and 33.02 minutes, respectively. The *t*-test rejects the null hypothesis that those average clearance times are equal at the 95 percent significant level. The results further confirm that the prompt response of an incident response team with sufficient traffic management expertise can indeed contribute to a reduction in the overall incident clearance duration and the resulting impacts.

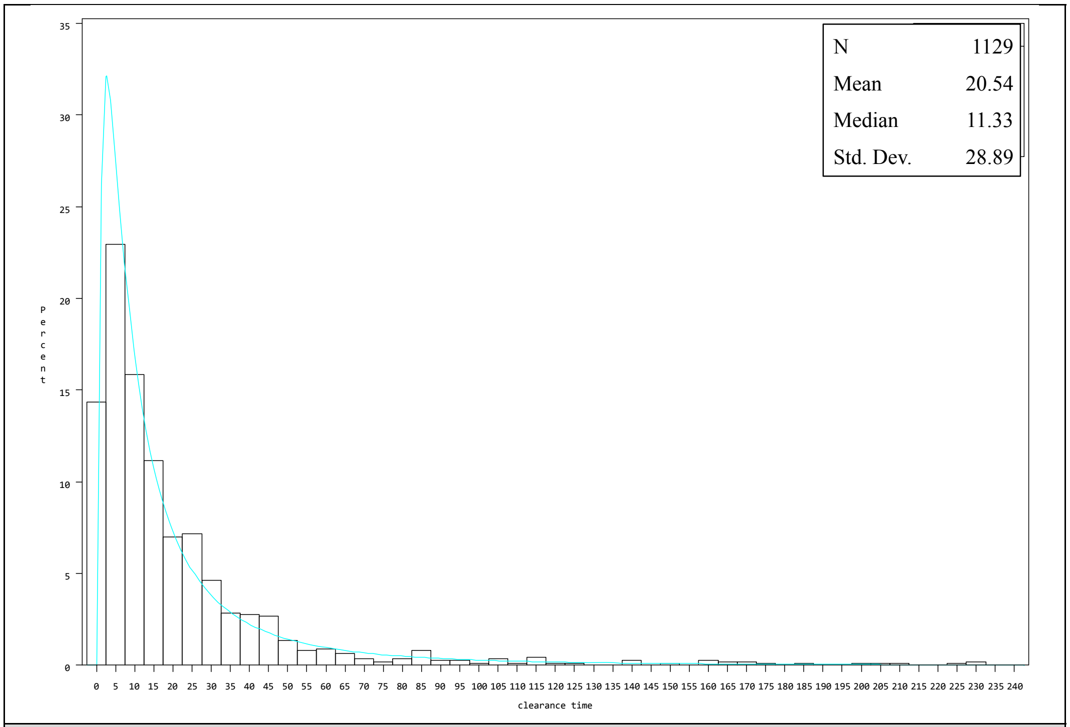
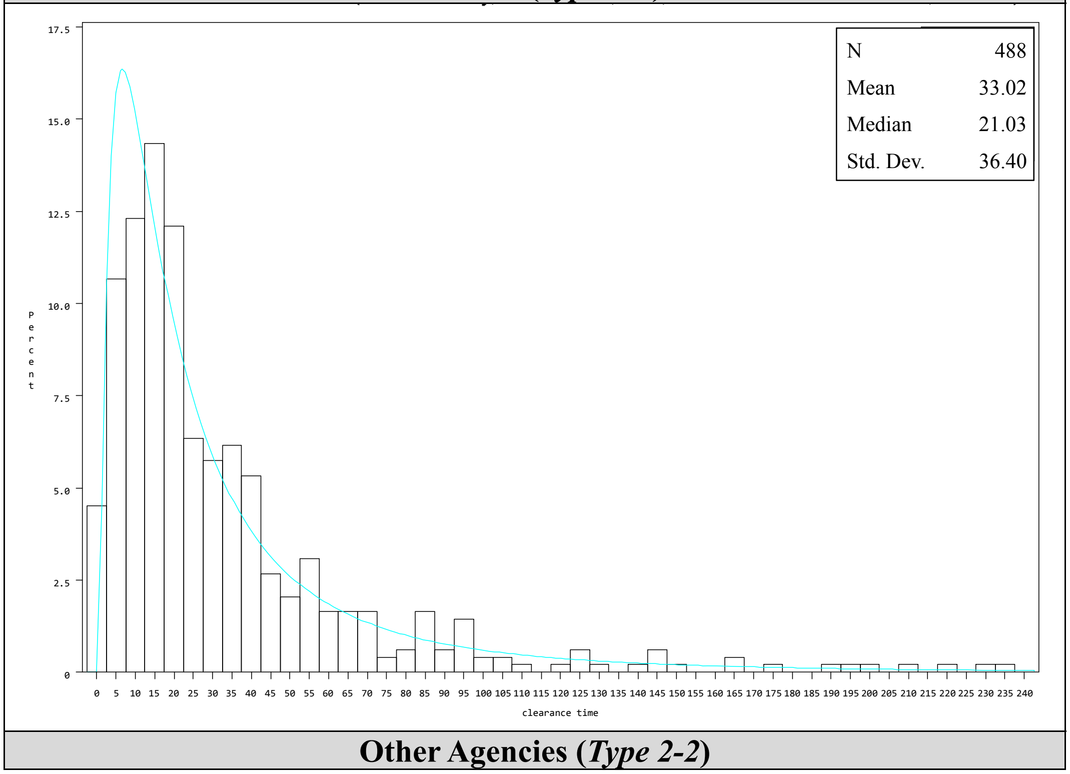


CHART (*Type 2-1*)



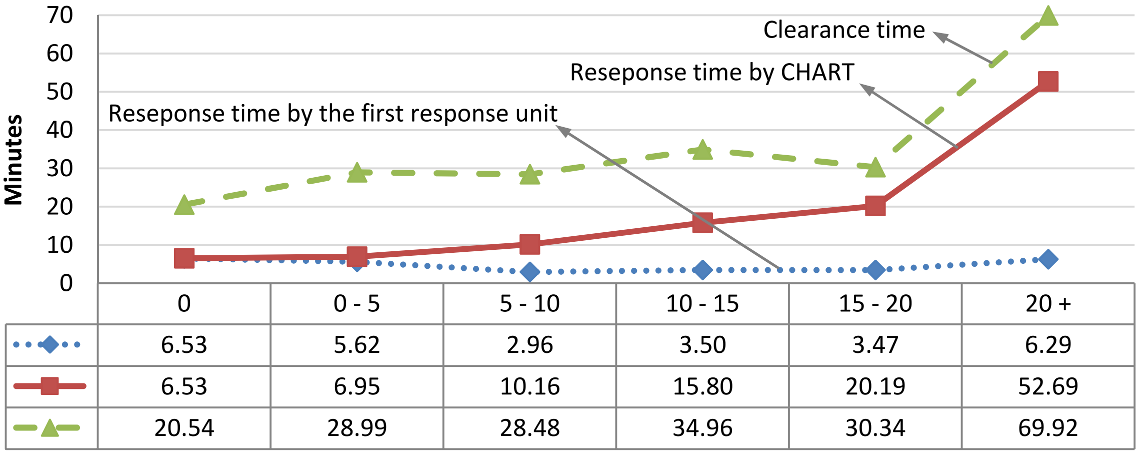
Other Agencies (*Type 2-2*)

Note: 1. Data include incidents occurring during a.m. peak hours (7 a.m. – 9:30 a.m. on weekdays) in Maryland in 2012.

2. The analysis only includes clearance times between 1 minute and 4 hours.

FIGURE 2 Clearance Times (minutes) by the First Response Agency

Figure 3 illustrates the relationships between the incident clearance duration, response times by CHART, and response times by the first response unit. The graphical results reveal the interesting fact that the clearance time of a detected incident is likely to last much longer if CHART arrives much later than other agencies. More specifically, the response delays by CHART, compared with other agencies, are positively correlated with the resulting incident clearance times.



	0	0 - 5	5 - 10	10 - 15	15 - 20	20 +
◆	6.53	5.62	2.96	3.50	3.47	6.29
■	6.53	6.95	10.16	15.80	20.19	52.69
▲	20.54	28.99	28.48	34.96	30.34	69.92

* Note: 1. The horizontal axis represents that differences in arrived times between CHART and the first arriving agency, where *0* indicates that CHART arrives at the scene faster than others, and *0 - 5* indicates that CHART arrives within 5 minutes after the arrival of the first response agency.
2. Data include incidents occurring during a.m. peak hours (7 a.m. – 9:30 a.m. on weekdays) in Maryland in 2012.
3. The analysis only includes clearance times between 1 minute and 4 hours.

FIGURE 3 Relationships between Clearance Times and Delayed Response of CHART

Hence, one could conclude that the efficient response of an incident management team can indeed contribute to the reduction in not only the response time but also the clearance time. Moreover, the clearance time can be reduced significantly if the incident management team arrives at the scene faster than other agencies. For example, the average clearance times, for those with and without CHART involvement in TOC-3 are 22.47 and 24.40 minutes, respectively (see Table 1), but for those where CHART arrived earlier than others the statistics are 20.14 and 29.18 minutes, respectively.

However, it should be noted that not all incidents can be promptly responded by CHART due to their limited resources. Therefore, it is necessary to develop a strategy to optimally deploy available response units so as to maximize their contributions at both the incident response and clearance stages (equivalent to minimizing the incident impact), rather than merely emphasizing on the fast response.

TABLE 1 Average Clearance Time (minutes) by Response Agencies in Operation Centers

		TOC-3	TOC-4	TOC-7	AOC	SOC
CHART not involved		24.40	29.06	39.92	26.42	60.04
CHART involved		22.47	22.53	26.12	17.55	44.23

⇓

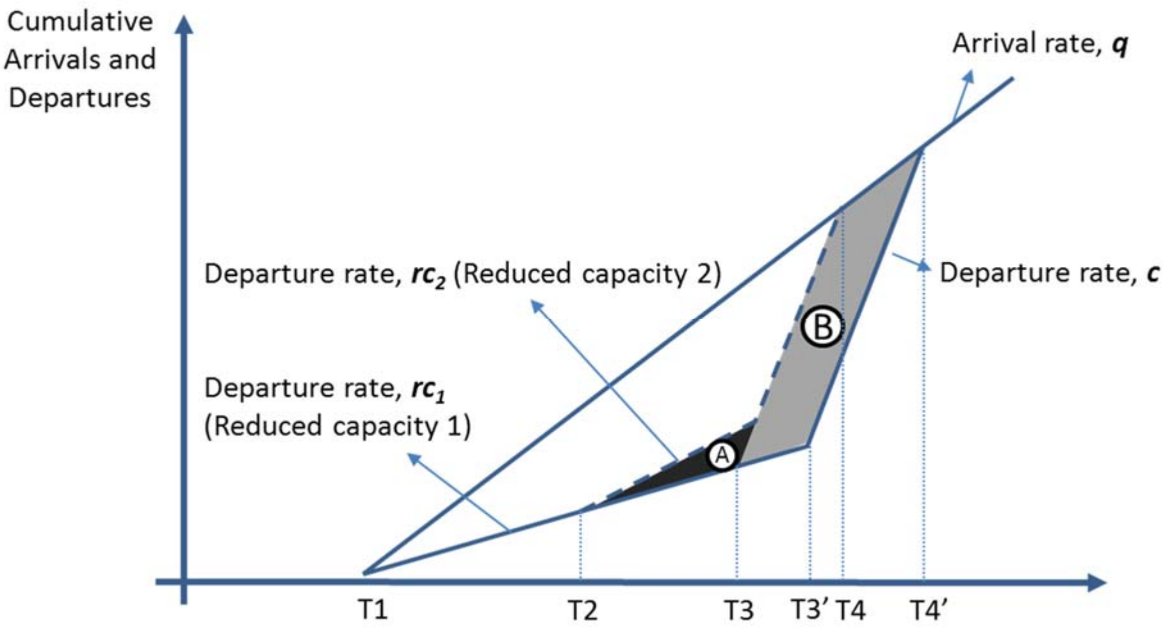
First Responder	CHART	20.04	19.80	21.06	12.89	35.99
	Others	29.18	32.09	41.43	22.47	54.95

Note: 1. This analysis only includes Maryland incidents occurring during a.m. peak hours (7 a.m. – 9:30 a.m. on weekdays) in 2012.
2. The analysis only includes clearance times between 1 minute and 4 hours.

4. METHODOLOGY

Relations between Incident Duration and Total Delay

To estimate the impact of incidents, this study uses the total delay induced by incidents as a measure of effectiveness (MOE). As reported in the literature (*49, 50*), the incident-induced delay varies with several key factors, including traffic demand, freeway capacity, reduced freeway capacity, and especially incident duration. As illustrated in Figure 4, prompt incident response and efficient clearance can reduce the incident cleared time from *T3’* to *T3*, and improved the reduced freeway capacity from rc_1 to rc_2. As the results, the recovery time would be reduced from *T4’* to *T4*, so as the total delay, as shown in the shaded area (*A* and *B*). Since the data to support the delay reduction, i.e., the area *A*, due to the increased departure rate (rc_2) are not available, this study has focused mainly on the reduced delay contributed by the reduced incident clearance time.



T1: incident starting time
T2: arrival time of the response unit
T3: incident cleared with the assist of CHART
T3’: incident cleared without the assist of CHART

T4: recovery time due to the assist of CHART
T4’: recovery time without the assist of CHART
q: arrival rate
c: departure rate
rc_1: reduced departure rate
rc_2: increased departure rate by the assist of CHART

FIGURE 4 Reduced Incident Delay due to Effective Incident Response and Management

Model Formulations

To formulate the model this study assumes that response units will stay at their assigned locations and will be dispatched after an incident being detected. They shall return to their originally designated locations after the incident being cleared. Additional assumptions for modeling are stated as follows:

- Every freeway segment is covered by one unit.
- The number of incidents on each sliced highway segment i is distributed uniformly.
- Response units are allowed to travel on shoulders during incident management periods.

The nodes and links in the model formulations denote the freeway exits and roadway segments, respectively. The travel times from the assigned locations to incident site are measured from the node of the assigned locations to the middle point of segments where the incident occurred. Notations used in hereafter are summarized as follows:

- $G(N, A)$: Network of freeways, where N and A are the sets of nodes and links
- i and j: Index for nodes. $i, j \in N$
- x_{ij}: Binary decision variable, indicating if a node j is covered by a unit at a node i
- y_i: Binary decision variable, indicating if a unit stays at a node i
- f_j: Incident frequency at a node j
- t_{ij}: Travel time from i to j
- d_j: Predicted delay from incidents occurring at a node j
- T_{ij}: Incident duration equal to the sum of response time and clearance time
- α: Proportion of incidents served by freeway incident management teams at a given time
- β: Proportion of incidents responded by freeway incident management teams first at a given time
- RT_1: average minimum response time by other agencies in *Type 1*
- RT_2: average minimum response time by other agencies in *Type 2-2*
- CT_1: Clearance times of incidents that freeway incident management teams are not involved in response and clearance
- CT_{2-1}: Clearance times of incidents that freeway incident management teams respond faster than any other agencies
- CT_{2-2}: Clearance times of incidents that freeway incident management teams respond later than other agencies
- $\overline{CT}_1$: Average clearance time of incidents that freeway incident management teams are not involved in their response and clearance
- $\overline{CT}_{2-1}$: Average clearance time of incidents that freeway incident management teams respond faster than any other agencies

- $\overline{CT}_{2-2}$: Average clearance time of incidents that freeway incident management teams respond later than other agencies
- q_j: Traffic volume at a node j
- c_j: Capacity at a node j
- rc_j: Reduced capacity at a node j
- R: Available resources

To estimate the total incident delay this study categorizes incidents into the following three types: (1) incidents without the assist of freeway incident management teams (*Type 1*), (2) incidents that freeway incident management teams respond faster than any other agencies (*Type 2-1*), and (3) incidents that freeway incident management teams respond later than other agencies (*Type 2-2*).

The deployment model is formulated as follows:

object to $$\min_{x,y} \sum_i \sum_j x_{ij} \cdot f_j \cdot d_j(t_{ij}) \tag{1}$$

subject to

$$d_j(t_{ij}) = \frac{1}{2} {T_{ij}}^2 (q_j - rc_j) \left(\frac{c_j - rc_j}{c_j - q_j} \right) \qquad \forall (i,j) \in N \tag{2}$$

$${T_{ij}}^2 = \begin{cases} Type\ 1\text{:}\ \ (RT_1 + \overline{CT}_1)^2 + Var(CT_1)\,, & 1-\alpha \\ Type\ 2-1\text{:}\ \ (t_{ij} + \overline{CT}_{2-1})^2 + Var(CT_{2-1}), & \alpha, \beta \\ Type\ 2-2\text{:}\ \ (RT_2 + \overline{CT}_{2-2})^2 + Var(CT_{2-2})\ , & \alpha, 1-\beta \end{cases} \qquad \forall (i,j) \in N \tag{3}$$

$$\sum_i x_{ij} = 1 \qquad \forall\, i \in N \tag{4}$$

$$x_{ij} \le y_i \qquad \forall\, j \in N \tag{5}$$

$$\sum_i y_i \le R \tag{6}$$

$$x_{ij} = [0,1] \qquad \forall (i,j) \in N \tag{7}$$

$$y_i = [0,1] \qquad \forall\, i \in N \tag{8}$$

where f_j denotes the incident frequency at location j and t_{ij} denotes the travel time from locations i to j. The model aims to optimally allocate available resources by minimizing the total delay of incidents occurring in the target network.

Constraint (2) formulates the potential total delay induced by incidents on node j based on the widely used method (*49-51*) which points out that the total delay is a convex function of incident duration. Taking the stochastic nature of incident duration into account, T_{ij}^2 can be expressed in $(\overline{T_{ij}})^2 + Var(T_{ij})$ (*49, 50*). Constraint (3) describes the input of incident duration for each type. The average response time from the historical data are used for the response times for *Type 1* and *Type 2-2* (i.e., non-CHART response), whereas the travel time by CHART from its station i to an incident site j is used as a response time for *Type 2-1*. The average clearance time for each type is estimated with the CHART II Database.

Constraint (4) requires that every freeway segment i must be served by one response unit. Constraint (5) ensures that a response unit can only be dispatched from the location i if it stations there. Constraint (6) ensures that the total number of available response units is limited by available resources, R. In Constraint (7), x_{ij} equals 1 if a node j is covered by a unit at a node i, and 0 otherwise. In the last Constraint (8), y_i equals 1 if the station of a unit is the node i, and 0 otherwise.

5. EXPERIMENTAL DESIGN

Study Site

The study site is the highway network managed by CHART, TOC-7 local center, which covers I-270, I-70, and US-15 (see Figure 5), about 63-mile long with 30 exits. Currently, TOC-7 has 3 field operations units to manage incidents occurring on I-270 and I-70 as well as US-15 in Frederick, Carroll, and Howard Counties. They operate over 16 hours/day (5 a.m. – 9 p.m.) on weekdays. The proposed model is applied to determine the optimized locations for their response units over the responsible network so as to minimize the total delay during AM peak hours (7:00 – 9:30) on weekdays.

FIGURE 5 Study Segments of I-70, I-270, and US-50 in Maryland

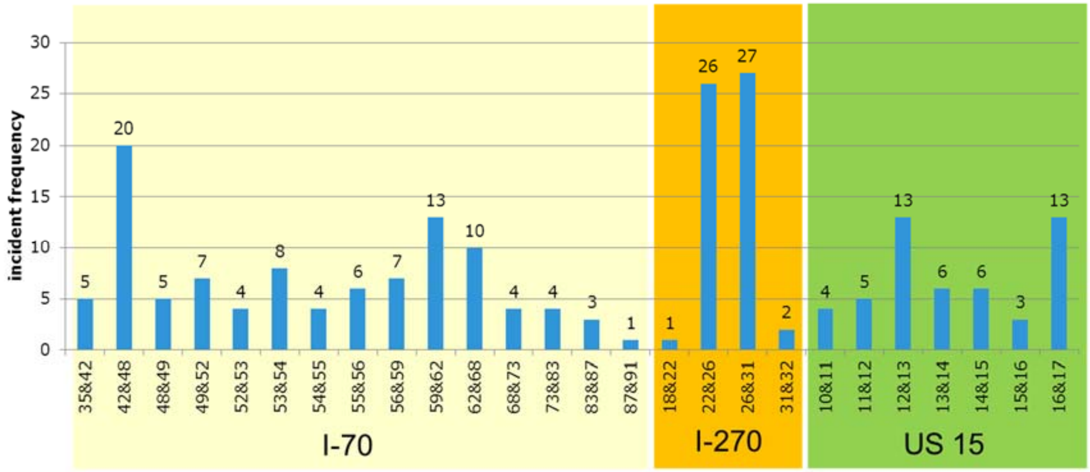


FIGURE 6 Average Annual Incident Frequency during AM Peak Hours by Location

We assume that incidents occurred along the highway segments, and response units are deployed at nodes (i.e., highway exits) for dispatching operations. The input parameters in the models are location specific for the study area. The following two major database sources are used to estimate key model parameters:

CHART II Database (data from Year 2010 to Year 2012) to obtain the following information:

- Incident frequency on freeway segment i (f_i) (Figure 6)
- Average response times for each type (RT_1 and RT_2)
- Average and variance of clearance times for each type ($\overline{CT}_k$ and $Var(CT_k)$, where k indicates one of *Type 1*, *Type 2-1*, and *Type 2-2*)
- α = 0.87 and β = 0.75
- Average number of lane closures to determine the reduced capacity (rc_j)

RITIS (Regional Integrated Transportation Information System) to obtain:

- Traffic volume (q_j)

In addition, the reduced capacity is estimated based on the average number of blocked lanes (from CHART II Database) and the guidelines from Highway Capacity Manual (52). The average speed by CHART between the station and the incident site is set as 5 mph lower than a speed limit, since they are allowed to use shoulders even in cases of congestion. The proposed models are solved with CPLEX, a state-of-the-art optimization software package.

Reference Models for the Comparative Study

The proposed model is evaluated by comparing with two existing strategies: (1) the dispatch strategy to minimize the average response times, and (2) the experience-based patrolling strategy operated by CHART. The key features of each strategy are summarized below:

Dispatching Strategy to Minimize the Average Response Time

The popular traditional p-median model (*10-12*) discussed in the literature review is used to compare the performance with the proposed model. This model assigns the optimal positions for available incident response units so as to minimize their average response time. The objective function of the model is $\min \sum_i \sum_j x_{ij} \cdot f_j \cdot t_{ij}$, where f_j denotes the incident frequency at node j, and t_{ij} represents the travel cost from the station i to the freeway segment j. The above constraints (4) – (8) in the section 4 are applied to this model under the same conditions.

Experience-based Patrolling Strategy

Currently, CHART is operated with the experience-based patrolling strategy that is to pay more attentions to highway segments with high incident frequency or high traffic volume. A brief description of their current practice is stated below:

- The entire network of coverage is divided into several sub-networks. The scheme to divide the target network varies over time, based on the spatial distribution of total incidents in the historical data and the real-time traffic volumes.
- Each available unit is then assigned by the supervisor to patrol those segments within each sub-network.
- They respond incidents either by their own detection or after receiving a call from the operation center.
- The response is on the first-come-first-serve basis, unless major incidents such as personal injuries or fatalities occur.

6. RESULT ANALYSIS

Model Results

Table 2 compares the optimal stationary positions and assigned coverage for available response units under these three strategies – minimizing the total delay (the proposed model), minimizing the average response time, and the CHART current practice. To compare the impact of the fleet sizes on the effectiveness of each strategy, Figures 7 and 8 illustrate their resulting travel times and delays under the fleet sizes from 2 to 7.

TABLE 2 Stations and Coverage Assigned for Available Response Units by Strategy

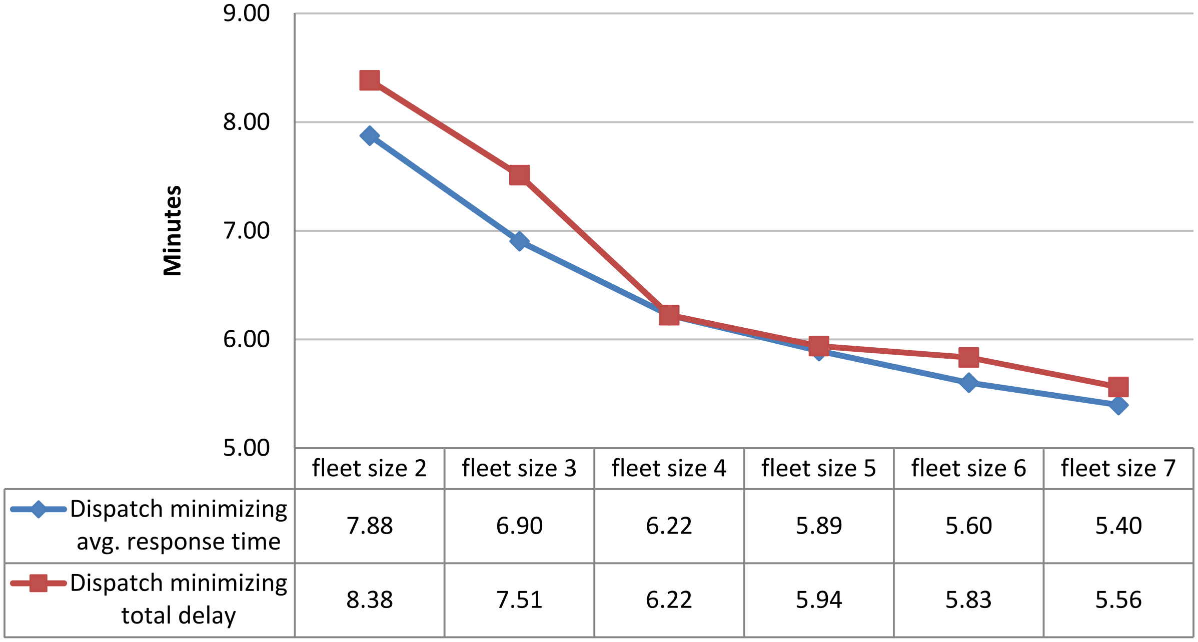
(a) Assignments of Stations

No. of Units Available	Assigned Stations (Exits) by		
	Dispatch minimizing total delay	Dispatch minimizing avg. response time	CHART practice
2	I-70: 42 and 53	I-70: 52 and 68	N/A
3	I-70: 42, 53 / I-270: 26	I-70: 52, 68 / I-270: 22	Patrolling all segments
4	I-70: 42, 52, 68 / I-270: 26	I-70: 42, 52, 68 / I-270: 26	N/A
5	I-70: 42, 53, 68 / I-270: 26 / US-15: 16	I-70: 42, 52, 62, 80 / I-270: 26	
6	I-70: 42, 48, 53, 68 / I-270: 26/ US-15: 16	I-70: 42, 52, 62, 80 / I-270: 26 / US-15: 17	
7	I-70: 42, 48, 53, 62, 82 / I-270: 26 / US-15: 16	I-70: 42, 52, 62, 68, 80 / I-270: 26 / US-15: 17	

(b) Assignments of Coverage

No. of Units Available	Assigned Coverage by		
	Dispatch minimizing total delay	Dispatch minimizing avg. response time	CHART practice
2	(35 - 42 on I-70), (others)	(others), (62 - 87 on I-70)	N/A
3	(35 - 42 on I-70), (others), (22 - 26 on I-270)	(others), (62 - 87 on I-70), (22 - 26 on I-270)	Patrolling all segments
4	(35 - 42 on I-70), (others), (62 - 87 on I-70), (22 - 26 on I-270)	(35 - 42 on I-70), (others), (62 - 87 on I-70), (22 - 26 on I-270)	N/A
5	(35 - 42 on I-70), (others), (62 - 87 on I-70), (22 - 26 on I-270), (13-17 on US-15)	(35 - 42 on I-70), (others), (59 - 68 on I-70), (73 - 87 on I-70), (22 - 26 on I-270)	
6	(35 - 42 on I-70), (48 - 59 on I-70), (others), (62 - 87 on I-70), (22 - 26 on I-270), (13-17 on US-15)	(35 - 42 on I-70), (others), (59 - 68 on I-70), (73 - 87 on I-70), (22 - 26 on I-270), (14 - 17 on US-15)	
7	(35 - 42 on I-70), (48 - 59 on I-70), (others), (62 - 73 on I-70), (76 - 87 on I-70), (22 - 26 on I-270), (13-17 on US-15)	(35 - 42 on I-70), (others), (59 - 62 on I-70), (68 - 73 on I-70), (76 - 87 on I-70), (22 - 26 on I-270), (14 - 17 on US-15)	

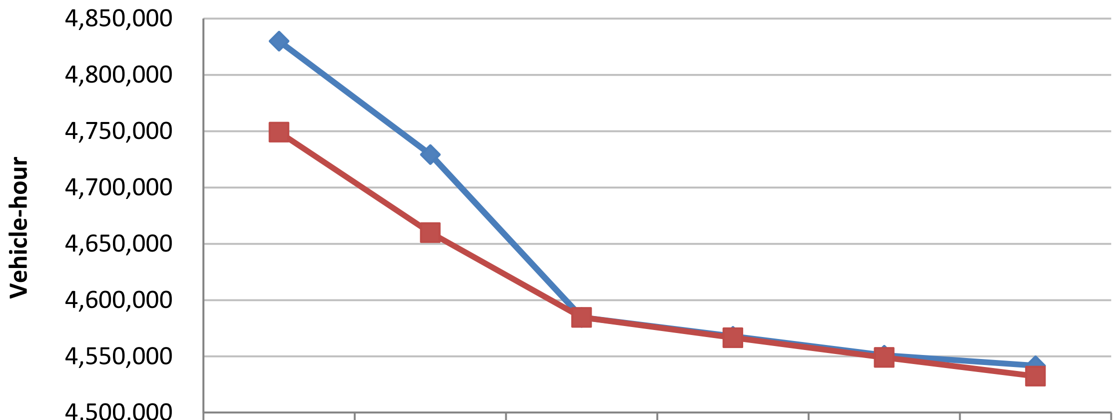
As shown from these figures, both estimated average response time and total delay drastically decrease by adding a unit until reaching the size of 4 units, and the rate of decrease becomes less significant. In Figure 7, as expected, the average response time with the strategy of minimizing total delay is larger than that under the strategy of minimizing the average response time over most fleet sizes explored in this study. The difference progressively decreases, and exhibits none at the fleet size of 4, but it increases again as the fleet size increases. For the fleet size of 3 that CHART currently operates, the average response time by CHART's current practice is 7.79 minutes which are 3.6 percent and 11.4 percent larger than those by the proposed model (7.51 minutes) and the traditional *p*-median model (6.90 minutes), respectively.



	fleet size 2	fleet size 3	fleet size 4	fleet size 5	fleet size 6	fleet size 7
◆ Dispatch minimizing avg. response time	7.88	6.90	6.22	5.89	5.60	5.40
■ Dispatch minimizing total delay	8.38	7.51	6.22	5.94	5.83	5.56

FIGURE 7 Average Travel Times (in minutes) by Incident Response Strategy

Similar patterns are also shown in the measurement of total incident delay (see Figure 8). As expected, the total incident delay with the strategy of minimizing the total delay is less than the one by the strategy of minimizing the average response time over the fleet sizes of 2 to 7. The fleet sizes of 2 or 3 operated with the proposed strategy show a significant reduction in the total delay of 80,857 and 69,390 vehicle-hours per year, respectively, compared with the traditional *p*-median model. The differences in the total delay between these two strategies are insignificant at the fleet size of 4, and it gradually increases with more additional units. For the fleet size of 3 that CHART currently operates, the total delay by CHART's practice is 5,612,805 vehicle-hours which are 17 percent and 15.7 percent larger than those by the proposed model (4,659,967 vehicle-hours) and the traditional *p*-median model (4,729,356 vehicle-hours), respectively.



	fleet size 2	fleet size 3	fleet size 4	fleet size 5	fleet size 6	fleet size 7
◆ Dispatch minimizing avg. response time	4,829,998	4,729,356	4,584,707	4,567,920	4,551,095	4,541,785
■ Dispatch minimizing total delay	4,749,141	4,659,967	4,584,707	4,566,630	4,549,114	4,532,457

FIGURE 8 Total Delays (in vehicle-hour) by Incident Response Strategy

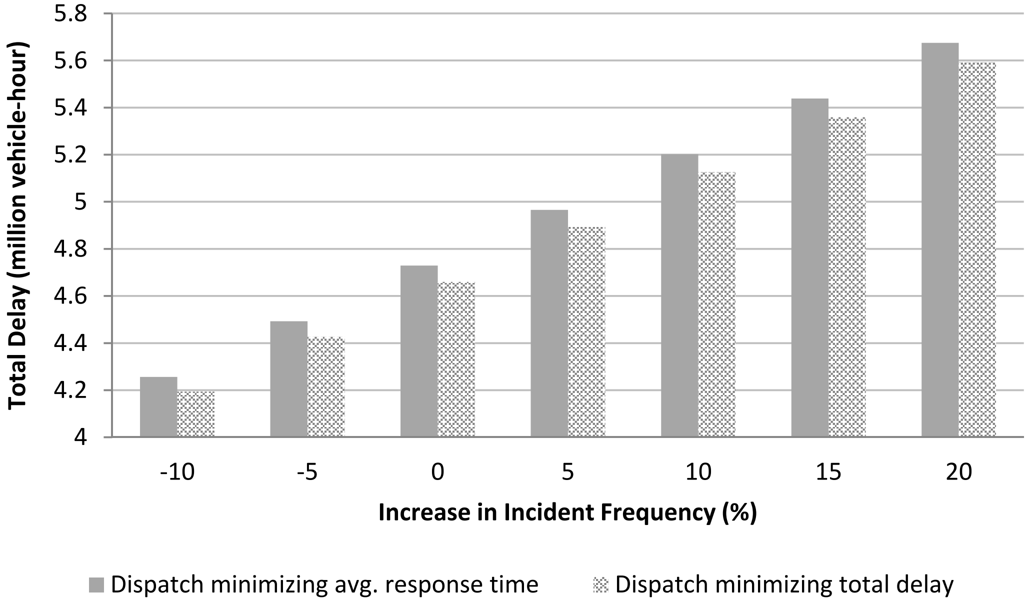
Based on these results, it seems that the proposed model, if implemented in the TOC-7 region of Maryland, can outperform the traditional deployment model of minimizing the response time with respect to reducing the total incident-induced delay. It can also outperform the CHART's current practice on both reducing average response time and the total delay. Although the results are based only on the incident data and traffic condition in one region of Maryland, the proposed model seems to offer an effective tool to improve the performance of the freeway incident management programs, especially if the primary concern is to minimize the total delay, fuel consumption, and emissions.

Sensitivity Analysis with respect to Key Parameters to Estimate Incident Delay

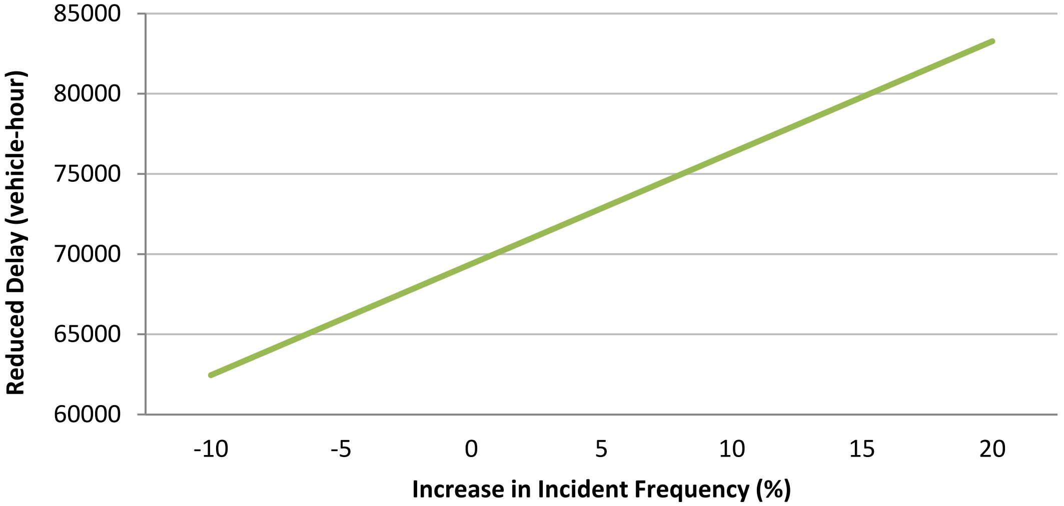
To investigate the performance of the proposed model in various network environments, this study has further conducted a sensitivity analysis with respect to key factors - incident frequency and traffic volume on the target network.

In Figure 9 (a), the estimated incident delay from both traditional and proposed strategies exhibits an increasing trend with the total incident frequency in the target network, given that all other factors remain unchanged. Overall, the delays based on the proposed model are lower than those from the traditional *p*-median model through all examined incident frequencies. The magnitude of the reduction increases linearly, as shown in Figure 9 (b), indicating the proposed model's superior performance regardless of the incident frequency.

(a) Incident Delay under Various Incident Frequencies



(b) Reduced Incident Delay by the Proposed Model for Various Incident Frequencies

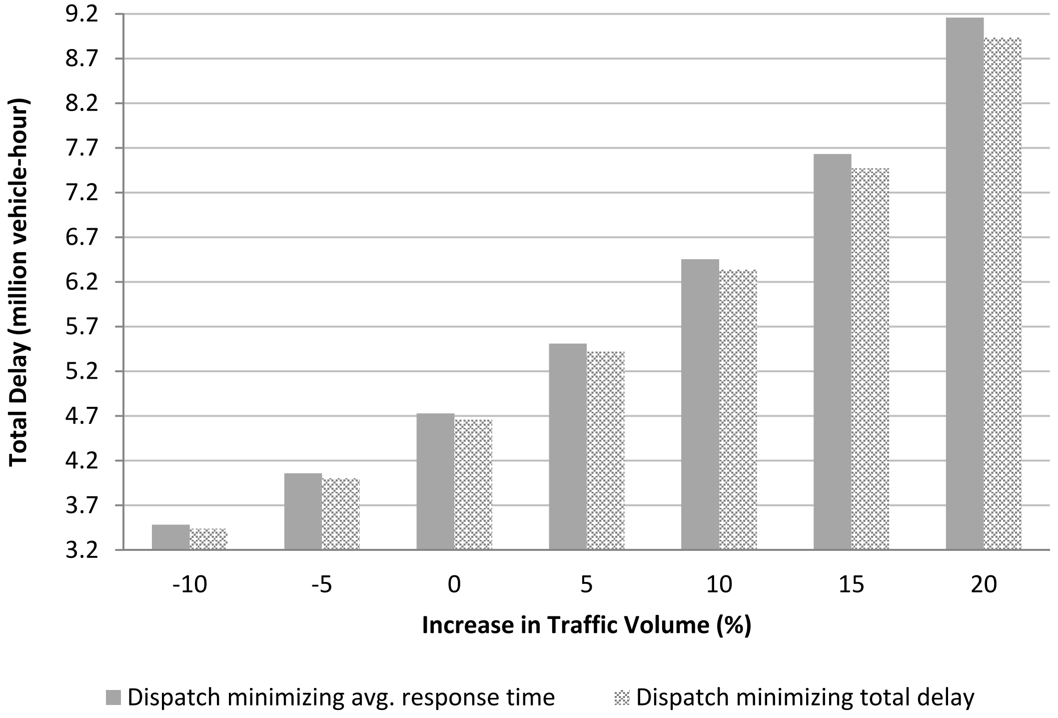


* Note: the horizontal axis represents the increase or decrease in the incident frequency in percentage from the value used for the empirical study. ***0*** and ***5*** indicates the incident frequency used in the case study and 5 percent increase from it, respectively, and so on.

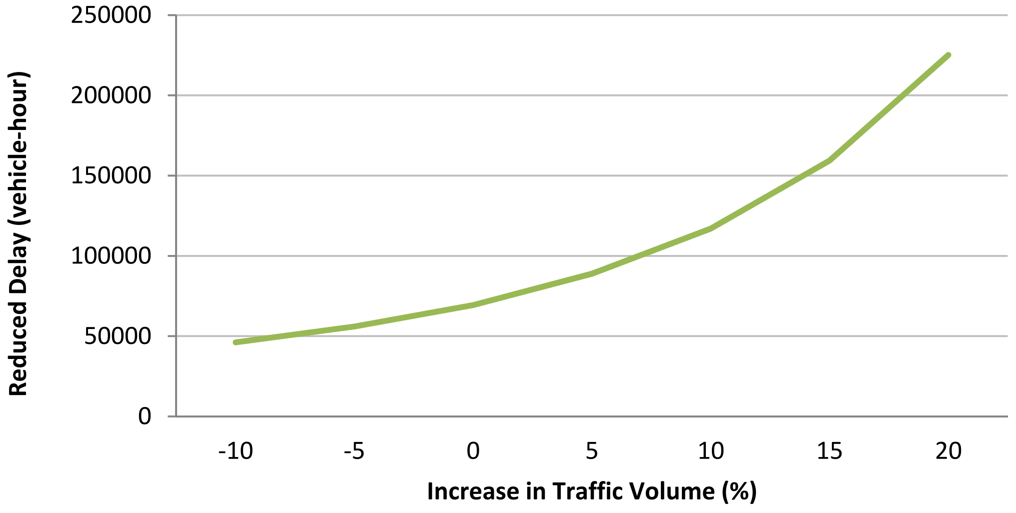
FIGURE 9 Model Results under Various Incident Frequencies

Similarly, a range of traffic volumes has been examined to assess their impacts on the resulting incident delay. Figure 10 (a) exhibits that the estimated incident delays from both traditional and proposed strategies increase with the traffic volume in the target network if all other factors are at the same level. The delays based on the proposed model remain lower than those from the traditional model over all listed traffic volumes, and the magnitude of the reduction exponentially increases, as displayed in Figure 10 (b).

(a) Incident Delay under Various Traffic Volumes



(b) Reduced Incident Delay by the Proposed Model for Various Traffic Volumes



* Note: the horizontal axis represents the increase or decrease in the incident frequency in percentage from the value used for the empirical study. ***0*** and ***5*** indicates the incident frequency used in the case study and 5 percent increase from it, respectively, and so on.

FIGURE 10 Model Results by Various Traffic Volumes

The results from the above sensitivity analysis further confirm that the developed model can outperform the traditional deployment models with respect to minimizing the total incident delay in most scenarios. Thus, the proposed deployment strategy offers the potential for use in different highway networks.

7. CONCLUSIONS

This study has proposed an integer programming model to deploy incident response units at optimal locations within their responsible service area. It is motivated by various studies discussing that successful freeway incident management programs noticeably contribute to alleviating the non-recurrent congestions not only by prompt response, but also by efficient incident clearance and traffic management.

The incident data from Maryland clearly show that the average clearance time of incidents operated by Maryland incident management program (CHART) is shorter than the one without CHART. Furthermore, the incidents first responded by CHART present a shorter average clearance time than those responded by CHART but arriving at the scene later than other agencies. It is also found that the average clearance time is likely to increase if the average response time by CHART increases, even if other agencies respond to the incident faster than CHART. These findings confirm that the freeway incident management program plays an important role in expediting the incident clearance and consequently reducing the incident delay.

For this sake, the proposed model adopts minimizing the total delay as the objective function to optimize the deployment stations for response units. This is different from most studies in the literature which focus on minimizing total/average response times. The empirical study conducted for various fleet sizes from 2 to 7 using CHART II Database shows that the total incident delays with the proposed model are smaller than those with the traditional deployment model and the current practice by CHART. Especially for the fleet size 3, which is the current fleet size for CHART in the study area, the developed model can reduce the average response time and total incident delay by 3.6 percent and 17 percent, respectively, from the CHART's current practice.

To ensure the performance robustness, this study has further conducted the sensitivity study to evaluate the proposed model under various traffic volumes and incident frequencies. The extensive numerical results confirm that the proposed model can yield the smaller total incident delay than the traditional *p*-median model for all experimental scenarios. Hence, the proposed model seems to offer the potential for use in different regions of Maryland's highway networks, and possibly be applied in different states with similar patterns of incidents. Note that the reduced delays along with the byproducts of reduced fuel consumptions and emissions due an efficient incident management program could produce significant socioeconomic and environmental benefits.

REFERENCES

1. FHWA White Paper. *An Initial Assessment of Freight Bottlenecks on Highways*. Federal Highway Administration, 2005, http://www.fhwa.dot.gov/policy/otps/bottlenecks/bottlenecks.pdf
2. Lindley, J. The Urban Freeway Congestion Problem, *Transportation Research Circular* 344, TRB, National Research Council Washington, D.C., 1989.
3. Skabardonis, A., K. Petty, P. Varaiya and R. Bertini. *Evaluation of the freeway service patrol (FSP) in Los Angeles*, California PATH Research Report, Report UCB-ITS-PRR-98-13, University of California, Berkeley, 1998.
4. Latoski, S. P., R. Pal, and K. C. Sinha. *An Evaluation of the Cost Effectiveness of the Hoosier Helper Program and Framework for the Design of ITS Optimal System Configuration, Phase 1*. Paper 346. FHWA/IN/JTRP-97/09, Joint Transportation Research Program, 1998. http://docs.lib.purdue.edu/jtrp/346.

5. Khattack, A. J., and N. Rouphail, *Incident Management Assistance Patrols: Assessment of Investment Benefits and Cost.* Carolina Transportation Program Report, Report NCDOT 2003-06, NC State University, January 2004.
6. Haghani, A., D. Iliescu, M. Hamedi, and S. *Yang. Methodology for Quantifying the Cost Effectiveness of Freeway Service Patrols Programs - Case Study: H.E.L.P. Program.* Technical Report. 2006.
7. Chou, C., and E. Miller-Hooks. Benefit-Cost Analysis of Freeway Service Patrol Programs: Methodology and Case Study. *Advances in Transportation Studies,* 2009.
8. Lou, Y., Y. Yin, and S. Lawphongpanich. Freeway Service Patrol Deployment Planning for Incident Management and Congestion Mitigation. *Transportation Research Part C: Emerging Technologies,* Vol. 19, 2010, pp. 283–295.
9. Larson, R.C. and A.R. Odoni. *Urban Operations Research.* Prentice-Hall Inc. Englewood Cliffs, New Jersey, 1981.
10. Hakimi, S.L. Optimal Locations of Switching Centers and the Absolute Centers and Medians of a Graph. *Operations Research*, Vol. 12, 1964, pp. 450-459.
11. Chang, G and S. Rochon. *Performance Evaluation and Benefit Analysis for CHART.* Technical Report, Maryland State Highway Administration, 2012.
12. Olmstead, T. Pitfall to Avoid When Estimating Incident-Induced Delay by Using Deterministic Queuing Models. *Transportation Research Record: Journal of the Transportation Research Board* No. 1683, TRB, National Research Council, Washington, D.C., 1999, pp. 38–46.
13. Weber, A. Uber den Standort der Industrie (Alfred Weber’s Theory of the Location of Industries), Univ. of Chicago, Chicago. 1929.
14. Toregas, C., R. Swain, C. ReVelle., C. Bergman. The location of emergency service facilities. Operations Research, 19(6), 1971, pp. 1363–1373.
15. Church, R. and C. ReVelle. The maximal covering location problem. *Papers of the Regional Science Association*, 32, 1974, pp. 101–118.
16. White, J. and K. Case. On covering problems and the central facility location problem. *Geographical Analysis*, 281(6), 1974, pp. 281–293.
17. Schilling, D., D. Elzinga, J. Cohon, R. Church, and C. ReVelle, The TEAM/FLEET models for simultaneous facility and equipment siting. *Transportation Science*, 13, 1979, pp. 163–175.
18. Eaton, D.J., M. S. Daskin, D. Simmons, B. Bulloch, and G. Jansma. Determining emergency medical deployment in Austin, Texas. *Interfaces*, 15(1), 1985, pp. 96–108.

19. Chapman, S.C. and J. A.White. Probabilistic formulations of emergency service facilities location problems, Presented at the ORSA/TIMS Conference, San Juan, Puerto Rico.1974
20. Daskin, M. The maximal expected covering location model: formulation, properties and heuristic solution. *Transportation Science*, 17(1), 1983, pp. 48–70.
21. Hogan, K., and C. S. ReVelle. Concept and Applications of Backup Coverage. Management Science, Vol. 32, 1986, pp. 1434–1444.
22. ReVelle, C. and K. Hogan. The maximum availability location problem. *Transportation Science*, 23, 1989a, pp.192–200.
23. Bianchi, C. and R. Church. A hybrid FLEET model for emergency medical service system design. *Social Sciences in Medicine*, 26(1), 1988, pp.163–171.
24. Batta, R., Dolan, J. and Krishnamurthy, N. (1989) The maximal expected covering location problem: revisited. *Transportation Science*, **23**, 277–287.

25. Goldberg, J., R. Dietrich, J.M. Chen, and M.G. Mitwasi. Validating and applying a model for locating emergency medical services in Tucson, AZ. *European Journal of Operational Research*, 49, 1990, pp. 308–324.
26. Repede, J.F. and J. J. Bernardo. Developing and validating a decision support system for locating emergency medical vehicles in Louisville, Kentucky. *Location Science*, 3(1), 1994
27. Zhu, S., W. Kim, and G-L Chang, Design and Benefit-Cost Analysis of Deploying Freeway Incident Response Units: A Case Study for Capital Beltway in Maryland, *Transportation Research Record*, in press, 2012
28. Schilling, D. Strategic facility planning: the analysis of options. *Decision Sciences*, 13, 1982, pp. 1–14.
29. Nair, R. and E. Miller-Hooks, Evaluation of relocation strategies for emergency medical service vehicles, *Transportation Research Record: Journal of the Transportation Research Board* No. 2137, 2009, pp.63-73.
30. Sathe, A., and E. Miller-Hooks. Optimizing Location and Relocation of Response Units in Guarding Critical Facilities. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1923, Transportation Research Board of the National Academies, Washington, D.C., 2005, pp. 127–136.
31. Birge, J. R., and F. Louveaux. Introduction to stochastic programming, Springer-Verlag, New York. 1997.
32. Sylvester, J.J. A question in the geometry of situation. *Quarterly Journal of Pure and Applied Mathematics,* Vol.1, 1857.
33. ReVelle, C. and K. Hogan, K. The maximum reliability location problem and a reliable p-center problem: derivatives of the probabilistic location set covering problem. *Annals of Operations Research*, 18, 1989b, pp. 155–174.
34. Hochbaum, D.S. and A. Pathria. Locating centers in a dynamically changing network and related problems. *Location Science*, 6, 1998, pp. 243–256.
35. Talwar, M. Location of rescue helicopters in South Tyrol, presented at the 37th Annual ORSNZ Conference, Auckland, New Zealand. 2002.
36. Garfinkel, R.S., A. W. Neebe, and M. R. Rao. The m-center problem: minimax facility location. *Management Science*, 23, 1977, pp. 1133–1142.
37. Handler, G.Y. *P*-center problems, *Discrete Location Theory*, Mirchandani, P.B. and Francis, R.L. (eds.), J.Wiley, New York, NY, 1990, pp. 305–347.
38. Brandeau, M.L., S. S. Chiu, S. Kumar, and T. A. Grossman. Location with market externalities, *Facility Location: A Survey of Applications and Methods*, Drezner, Z. (ed.), Springer-Verlag, New York, NY, 1995, pp. 121–150.
39. Daskin, M. A new approach to solving the vertex *P*-center problem to optimality: algorithm and computational results. *Communications of the Japanese OR Society*, 9, 2000, pp. 428–436.
40. Current, J., M. Daskin, and D. Schilling. Discrete network location models, *Facility Location: Applications and Theory*, Drezner, Z. and Hamacher, H.W. (eds.), Springer-Verlag, New York, NY, 2001, pp. 83–120.
41. ReVelle, C. and R. W. Swain, R.W. Central facilities location. *Geographical Analysis*, 2, 1970, pp. 30–42.
42. Carson, Y. and R. Batta. Locating an ambulance on the Amherst campus of the State University of New York at Buffalo. *Interfaces*, 20, 1990, pp. 43–49.
43. Mandell, M.B. A *P*-median approach to locating basic life support and advanced life support

units, presented at the CORS/INFORMS National Meeting, Montreal, Canada. 1998.

44. Mirchandani, P.B. Locational decisions on stochastic networks. *Geographical Analysis*, 12, 1980, pp. 172–183.
45. Serra, D. and V. Marianov. The *P*-median problem in a changing network: the case of Barcelona. *Location Science*, 6(1), 1999, pp. 383–394.
46. Haghani, A., H. Hu, and Q. Tian. Optimization Model for Real-Time Emergency Vehicle Dispatching and Routing. Presented at 82nd Annual Meeting of the Transportation Research Board, Washington, D.C., 2003.
47. Yang, S., M. Hamedi, and A. Haghani. Integrated Approach for Emergency Medical Service Location and Assignment Problem. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1882,* Transportation Research Board of the National Academies, Washington, D.C., 2004, pp. 184–192.
48. Yang, S., M. Hamedi, and A. Haghani. Online Dispatching and Routing Model for Emergency Vehicles with Area Coverage Constraints. In Transportation Research Record: Journal of the Transportation Research Board, No. 1923, Transportation Research Board of the National Academies, Washington, D.C., 2005, pp. 1–8.
49. Olmstead, T. Pitfall to Avoid When Estimating Incident-Induced Delay by Using Deterministic Queuing Models. *Transportation Research Record: Journal of the Transportation Research Board* No. 1683, TRB, National Research Council, Washington, D.C., 1999, pp. 38–46.
50. Li, J., C-J Lan, and X. Gu, Estimation of Incident Delay and Its Uncertainty on Freeway Networks. *Transportation Research Record: Journal of the Transportation Research Board* No. 1959, Transportation Research Board of the National Academies, Washington, D.C., 2006, pp. 37–45.
51. Skabardonis, A., H. Noeimi, K. Petty, D. Rydzewski, P. Varaiya, and H. Al-Deek. *Freeway Service Patrol Evaluation.* Report UCB-ITS-PRR-95-5. California PATH Program, Institute of Transportation Studies, University of California, Berkeley, 1995.
52. Transportation Research Board, *Highway Capacity Manual 2000*. Transportation Research Board, National Research Council, Washington, D.C., 2000.