Location configuration design for Dynamic Message Signs under stochastic incident and ATIS scenarios

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Abstract

This paper proposes a methodology for deploying permanent Dynamic Message Signs (DMS) in a vehicular traffic network. Of particular interest is the planning problem to optimize the number of DMS to deploy in conjunction with Advanced Traveler Information Systems (ATIS), operating and maintenance cost of DMS, and incident-related user cost under random traffic incident situations. The optimal DMS location design problem discussed herein is formulated as a two-stage stochastic program with recourse (SPR). A Tabu search algorithm combined with dynamic traffic simulation and assignment approaches are employed to solve this problem. A case study performed on the Fort-Worth, Texas network highlights the effectiveness of the proposed framework and illustrates the affect factors such as demand, network structure, DMS response rate, and incident characteristics have on the solution. The numerical results suggest that designing and deploying DMS and ATIS jointly is more cost-effective and efficient than the sequential build-out of the two from the system management perspective.

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1. Introduction

Dynamic Message Signs (DMS), also known as Variable Message Signs (VMS), are one of the primary Intelligent Transportation Systems (ITS) components. They are used to disseminate traffic information and roadway condition to drivers in order to assist them in making route choice decisions, particularly under disturbed traffic conditions. To date, transportation agencies have relied mostly on the Manual on Uniform Traffic Control Devices (MUTCD) (FHWA, 2000) for guidelines on the number of DMS to use and where to place
them. The MUTCD design parameters consist mainly of sight distance, visibility, legibility, and geometry. Network performance factors have not been considered due to limited research findings available in this area.

The configuration of the DMS has direct bearing on the network performance. Poorly placed DMS may offer limited benefits, and in some instances, it could even be counterproductive. For example, if a DMS is placed at locations where diversion of vehicles induces severe congestion on the surface streets, drivers may question the quality of information provided by the DMS and eventually become less sensitive to future DMS information, which in turn reduces the intended operational benefit.

Traffic volume and incident occurrence are critical factors to consider in determining the DMS location configuration. A key challenge is that incidents occur randomly. Each incident occurrence would entail using different DMS(s) to display incident information, which subsequently induces traffic re-distribution on both freeways and surface streets. Such information–traffic interactions are non-linear in nature and are difficult to represent analytically with sufficient operational accuracy for a general network. To date, the published literature does not appear to offer a comprehensive and theoretically sound treatment of this issue, though several studies have addressed partial aspects of the problem. Abbas and McCoy (1999) appears to be one of the first few published studies to address the DMS location configuration issue, which provides a good analytical view of this design problem. In that study, the authors proposed a genetic algorithm that searches for the best DMS locations. Their goal was to find a location configuration that maximizes the number of vehicles traveling past the signs. Their study measures location benefits as the approximate number of sign-traversing vehicles, obtained using a simplified static approach. It however did not consider diversion induced by the signs, nor did it account for the resulting traffic (from diversion) on both freeways and adjacent surface streets.

Other DMS studies have focused on the impact of various display content (Wardman et al., 1997; Ullman and Dudek, 1999; Dudek et al., 2001; Durkop and Dudek, 2001), applying certain control logic for a set of messages (Mammar et al., 1997; Messmer et al., 1998; Finley et al., 2001), and investigating DMS-induced diversion behavior (Emmerink et al., 1996; Peeta et al., 2000; Peeta and Gedela, 2001; Chatterjee et al., 2002; Peng et al., 2004). Other than these important aspects of DMS operation, research that relates traffic dynamics and network-wide performance to DMS location planning remains limited.

The principal goal of this paper is to present a methodology for strategically locating a finite number of DMS, with the objective of reducing the life cycle cost of the system by minimizing initial installation costs, operating and maintenance costs (O&M), and user costs associated with randomly occurring incidents that are not known a priori. A stochastic programming with recourse (SPR) model is proposed for the Stochastic Optimal DMS Location (SODMSL) problem. The stochastic programming approach has been proposed for a wide range of transportation problems (Vajda, 1972; Wets, 1989; Powell and Frantzeskakis, 1994; Waller and Ziliaskopoulos, 1998), though actual applications remain limited in practice. In the present study, a Tabu search procedure is employed to find solutions to the formulated problem due to the complexity introduced by non-linear traffic interactions which determine the value of the objective function for given DMS configurations and associated diversion. The recourse variables, DMS-induced diversion at candidate DMS locations, are modeled using the DYNASMART-P simulation-assignment model (Mahmassani et al., 2000).

An important issue uniquely addressed in this paper is the performance compensatory effect between DMS and pre-trip information (hereafter referred to as ATIS). The ATIS service considered in this study is the type that provides prevailing network traffic conditions (travel time, incident, weather, etc.) to users via a spectrum of channels such as Internet, television, radio, kiosks, etc. Such information may be accessed by certain trip-makers before the start of their trip and may alter the tripmakers’ departure time or route decisions (at the trip origin) in response to the reported traffic conditions (e.g. take an alternate route around the incident). The DMS system, on the other hand, facilitates route adjustment for those en-route drivers that are affected by the incident, causing traffic to be re-distributed locally. Although both sources of information affect only a subset of the traveling public, the resulting traffic dynamics could significantly affect network performance. Thus, the compensatory effect between the two information strategies suggests that a coordinated decision should be made with careful consideration of different information availability/compliance scenarios for optimal network performance and return of investment.

The rest of this paper is organized as follows. Section 2 provides the mathematical formulation of the SODMSL problem, followed by the description of the solution algorithm in Section 3. Section 4 describes the experiment design based on the Fort-Worth, Texas test network. Section 5 discusses the experiment results.
and their implications. Lastly, Section 6 summarizes the paper and provides remarks on future research directions.

2. Modeling concept and approach

In the adopted modeling approach, each DMS is defined to have an activation segment, which is the immediate downstream freeway section with a specific length (miles). A DMS is activated to display incident messages only if an incident occurs in the DMS’s activation segment. In other words, each DMS is associated with an activation segment; the incident activity in this region controls the activation of the DMS. It should be noted that the length of an activation segment depends on the actual state of practice, which may differ for different cities and countries. Such a setting reflects the engineering judgment that when an incident occurs, relevant DMS(s) should be activated to provide information to the traveling public who are likely to be affected. A DMS is usually not activated if the incident occurs upstream or far downstream. Fig. 1 illustrates a situation where an incident locates within the activation segments of DMS 1 and DMS 2; therefore, both DMS will be activated to display messages. DMS 3 is not activated because the location of the incident falls outside of DMS 3’s activation segment.

The DMS location configuration is an a priori planning decision. Once made, this decision would not be changed; however, the overall performance of the network is impacted by incidents occurring in a random fashion. An incident-activated DMS generates a recourse action by inducing diversion so that the impact of the incident is mitigated.

It is assumed in this work that an incident occurs during time interval \([T_s, T_e]\) and the activated DMS remain active during the same period. Also it is assumed that all individual vehicles departing at time \(t\) from origin \(i\) to destination \(j\) follow an initial path \(k \in K_{i,j}^{\text{ini}}\), which is typically a User Equilibrium (UE) path. The (UE) path set can be partitioned into those that traverse at least one active DMS node \((k \in K_{i,j}^{\text{act}})\), and those that do not \(k \in K_{i,j}^{\text{ini} \setminus \text{act}}\). \(K_{i,j}^{\text{ini} \setminus \text{act}}\) is defined as the path set such that \(k \in K_{i,j}^{\text{ini} \setminus \text{act}}\) \(\iff\) node \(m\) belongs to path \(k\). Also it is assumed that all individual vehicles departing at time \(t\) from origin \(i\) to destination \(j\) follow an initial path \(k \in K_{i,j}^{\text{ini}}\), which is typically a User Equilibrium (UE) path. The (UE) path set can be partitioned into those that traverse at least one active DMS node \((k \in K_{i,j}^{\text{act}})\), and those that do not \(k \in K_{i,j}^{\text{ini} \setminus \text{act}}\). \(K_{i,j}^{\text{ini} \setminus \text{act}}\) is defined as the path set such that \(k \in K_{i,j}^{\text{ini} \setminus \text{act}}\) \(\iff\) node \(m\) belongs to path \(k\). Assigning vehicles to these paths further characterizes the vehicles into two groups. Those which are assigned to path \(k \in K_{i,j}^{\text{ini} \setminus \text{act}}\) and arrive at node \(m\) at time \(t\) are considered as DMS Impact Group \(D\). All other vehicles (those which either take path \(k \in K_{i,j}^{\text{ini} \setminus \text{act}}\) or take path \(k \in K_{i,j}^{\text{ini} \setminus \text{act}}\) but arrive at node \(m\) at time \(t\) are considered non-DMS Impact Group \(ND\).

It can be seen that the definition of two groups cannot be determined a priori as the DMS arrival time \(t\) for the group \(D\) vehicles is unknown a priori and can only be determined based on loading and simulation of all vehicles.

Fig. 1. DMS location configuration modeling concept illustration.
vehicles because the DMS arrival time $t$ is influenced by a complex interaction between vehicles and system controls. This feature highlights the fundamental difference of the proposed dynamical approach versus the static approach employed in other studies. The traffic simulation model utilized in this research is DYNA-SMART-P (Mahmassani et al., 2000) because it has the capability to generate the initial UE paths and model traffic diversion at the active DMS nodes. During the simulation process, Group $ND$ vehicles are assumed to continue with their initial paths to their destinations without deviation because they are not considered to be affected by the incident and DMS. Group $D$ vehicles are subject to incident and DMS and therefore, are likely to re-route to other paths emanating from the DMS location.

2.1. Temporal and spatial modeling of incidents

Incident occurrence is considered to be a random process which follows certain temporal and spatial probability distributions. This distribution is best represented using actual field data. However, in this research, we assumed that the incident temporal occurrence follows the Poisson distribution, and the locations of these incidents follow the spatial Poisson distribution.

With the temporal peak-hour incident occurrence rate $\lambda_{t}$, the probability of having $n$ incidents occurring in a particular daily 2-h peak time period is as follows:

$$p(x = n) = \frac{\lambda_{t} \cdot e^{-\lambda_{t}}}{n!}$$

(1)

Based on the spatial Poisson distribution with $\lambda_{s}$ spatial density (occurrence rate per unit lane-mile), the probability of having $k$ incidents occurring on link $a$ given a total number of $n$ incidents occurring on the network is as follows:

$$h_{a}(x = k|n) = \binom{n}{k} \left( \frac{L_{a}}{L_{all}} \right)^{k} \left( 1 - \frac{L_{a}}{L_{all}} \right)^{n-k}$$

(2)

where $L_{a}$ is the lane-mile of link $a$, and $L_{all}$ is the total lane-mile of all freeway links on which incidents are to occur.

Simulation of the temporal and spatial occurrence of incident for the analysis addressed in this research follows the following steps:

1. Determine the cumulative mass function of Eq. (1) for $x = 0$ to $x = n$ and aggregate $x > n$ into one single event.
2. For each work day, draw a random number $\omega$ from a uniform distribution $U[0,1]$ and look up the number of incident occurrences for that day based on the outcome of $\omega$.
3. Repeat steps 1 and 2 for a pre-determined number of working days in a year.

The steps to applying Eq. (2) to model the spatial occurrence of incidents are discussed in TABU-DTA algorithm in Section 4.

2.2. Modeling of diversion at DMS

Given that research on the DMS diversion behavior is still at its infancy, the diversion mechanism adopted in this study is a simple and intuitive approach. During simulation, when a vehicle reaches an active DMS node, the simulation model determines whether the vehicle will respond to the DMS or not. Given a pre-specified response rate, the Monte Carlo approach is used to determine the response realization of individual vehicles. If a driver is a responsive driver, a set of routes that connects the DMS node to the driver’s destination is generated. This path set contains $K$ paths that are generated using a K-Shortest Path (KSP) algorithm. Choosing a path from such a path set reflects the fact that drivers are not necessarily aware of the best path at the time of diversion. Nonetheless, the chosen path is a good alternative route with reasonable travel time. Given the generated choice set, different approaches can be employed for modeling route choice. Since the focus of this paper is not on the route
choice behavior of DMS diversion, a simple uniform random selection method was used. That is, the driver randomly chooses a path from K paths and then continues on that path until he reaches his destination. In the event that multiple active DMS nodes exist and the chosen path traverse other active DMS nodes, the driver will go through the same decision process upon arriving at the next DMS location.

2.3. Modeling of ATIS

The particular type of ATIS service modeled in this research is a pre-trip information type of service that periodically updates traffic conditions to tripmakers. Monte Carlo approach is employed to determine whether the generated vehicles access ATIS prior to the trip departure on a pre-specified ATIS compliance rate. Once a tripmaker is determined to access ATIS, he/she obtains one of the K-shortest paths calculated based on the instantaneous travel time at the time of departure from the origin to the destination. Such K-shortest paths represent a set of reasonable paths from which a tripmaker chooses when accessing ATIS. Assigning paths in this manner gives a more realistic assessment of ATIS performance than giving the best path to tripmakers. During the incident occurring period, ATIS takes into account the traffic congestion in the vicinity of the incident and may recommend paths that bypass the incident sites. However, it is not necessary that all the ATIS-provided paths are away from the incident sites; the supplied paths are influenced by all vehicles in the network. In short, the ATIS service modeled provides drivers with the good paths taking into account incidents on the network at the time of departure.

2.4. Compensatory effect of DMS and ATIS service

The Advanced Traveler Information System, television, and radio are the most commonly used sources of traffic information. Tripmakers are likely to alter their originally planned departure time and/or route choice upon learning about incidents from the mentioned sources. Specifically, when an ATIS-information-receiving tripmaker’s original itinerary intersects with the incident site, he/she may choose another departure time with the same route, same departure time with a different route, or even a different departure time and different route in order to avoid the impact of the incident. If a set of tripmakers make such decisions, it could potentially lead to a reduction in traffic heading toward the incident site after the occurrence of the incident, and may consequently help alleviate the traffic congestion caused by the incident. This observation suggests that both DMS and ATIS jointly could improve traffic conditions, although they influence different set of tripmakers temporally or spatially – ATIS affects some tripmakers at the beginning of their trips, while DMS influences those traversing the activated DMS. The degree of improvement in network performance is directly related to how DMS are deployed and what type of ATIS services is used.

We postulate that the degree of network performance improvement for the same increment of the number of DMS diminishes with higher compliance rate to ATIS. Conversely, the degree of network performance improvement for the same increment of ATIS compliance rate diminishes with higher number of deployed DMS. Let the benefit of a DMS system be defined as the improvement in traffic condition using DMS compared to no-DMS at the time of incident. It is intuitive to postulate that a higher ATIS compliance will influence more tripmakers to adjust route and/or departure time at the start of the trip, which diminishes the benefit that could be obtained with DMS. In other words, let $B(\delta|\theta) = |T[\delta \cap \theta] - T[\theta]|/T[\theta]$, where $B(\delta|\theta)$ is the benefit measure of deploying $\delta$ number of DMS given ATIS compliance rate $\theta$. $T[\delta \cap \theta]$ is the network-wide MoE (e.g. average network-wide travel time) given $\delta$ number of DMS and ATIS compliance rate $\theta$ percent. $T[\theta]$ is the network-wide MoE given that only ATIS exists at compliance rate $\theta$

$$B(\delta|\theta_1) \geq B(\delta|\theta_2) \quad \forall \theta_2 \geq \theta_1$$

(3)

Similarly, the benefit of deploying ATIS at compliance rate $\theta$ given $\delta$ number of DMS can be defined as $B(\theta|\delta) = |T[\delta \cap \theta] - T[\delta]|/T[\delta]$, where $T[\delta]$ is the network-wide MoE given only $\delta$ number of DMS exist.

$$B(\theta|\delta_1) \geq B(\theta|\delta_2) \quad \forall \delta_2 \geq \delta_1$$

(4)

Inequalities (3) and (4) can be interpreted as the compensatory or substitution effect between the DMS and ATIS. The benefit of one system can be compensated other comparable systems. This study shows through
a numerical approach, that the inequalities (3) and (4) hold for the problem of interest. This analysis aims to not only highlight the compensatory effect between DMS and ATIS, but also to underscore the inter-dependence of various ITS components and stress that making component-based evaluation could lead to incomplete and misleading conclusions. Consequently, the need for a unified and integrated strategy for planning and deploying DMS taking into account available ATIS services is emphasized.

3. Model formulation

The problem of interest is formulated as a Stochastic Optimal DMS Location (SODMSL) problem. The objective is to minimize the total cost to the DMS planning agency (deployment, operating, and maintenance) and the average user costs. The user cost is defined as the monetary value of additional incident-related travel time compared to the no-incident situation. The user cost hence becomes a random variable because it is subject to random incident occurrence. The user cost is also influenced by the number and location of DMS, activation status related to incident, traffic diversion and resultant traffic dynamics, and the planning horizon of interest. As discussed previously, the user groups and respective user costs are evaluated using a simulation approach due to their complex user-to-user and user-to-system interaction. The decision variables are the number and locations where DMS are to be installed. In the present study, only locations along the highways are considered as potential locations for deploying DMS. Without loss of generality, the proposed method can be applied to both highway and arterials. The recourse decisions are represented by the traffic diversion induced by the active DMS given the number of DMS, their locations and the location of incidents.

The following model formulation is primarily for the purpose of depicting the general model structure. Functional constraints that are satisfied by the simulation model will only be noted; no detailed formulation will be presented. In the followings, first the notations and variables are introduced, and then the formulation is presented.

Notation

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Y$</td>
<td>decision variables, $Y = {y_n = {0, 1}</td>
</tr>
<tr>
<td>$N$</td>
<td>set of candidate DMS nodes</td>
</tr>
<tr>
<td>$V$</td>
<td>set of all vehicles that are modeled during period of interest. $D$: set of vehicles that traverse at least one activated DMS. $ND$: Set of vehicles that do not traverse any DMS. Each vehicle $v$ departs from origin node $i$ to destination node $j$ at time interval $\lambda$. $V = {D, ND}$</td>
</tr>
<tr>
<td>$d$</td>
<td>planning horizon (years)</td>
</tr>
<tr>
<td>$c_n$</td>
<td>construction cost for DMS $n$; different DMS may require different construction costs due to technology and construction requirements</td>
</tr>
<tr>
<td>$o_n$</td>
<td>net present value of the operating and maintenance (O&amp;M) cost for DMS $n$ over the planning horizon $d$. $o_n$ can be calculated as $o_n = \sum_{t=1}^{d} o'_n/(1 + r)^t$, where $o'_n$ is the O&amp;M cost at year $t$ and $r$ is the discount rate</td>
</tr>
<tr>
<td>$K_{i,j}^{\text{ini}}$</td>
<td>set of initial UE paths available for any vehicle leaving from origin $i$ to destination $j$, at time $\lambda$</td>
</tr>
<tr>
<td>$r_{i,j,k}^{\text{ini}}$</td>
<td>number of vehicles departing from origin $i$, to destination $j$ taking initial route $k$ at time $\lambda$</td>
</tr>
<tr>
<td>$\tilde{Q}$</td>
<td>set of time-dependent and random freeway link capacity $\tilde{Q} = {\tilde{Q}_a \mid \forall a \in A, t \in [T_s, T_e]}$, $T_s$: start time of incident and DMS, $T_e$: end time of incident and DMS. $A$: set of freeway links</td>
</tr>
<tr>
<td>$t_v$</td>
<td>experienced travel time for vehicles $v$ under the incident and DMS diversion situation</td>
</tr>
<tr>
<td>$T$</td>
<td>total system user cost under the no-incident situation</td>
</tr>
<tr>
<td>$\varphi$</td>
<td>hourly wage rate ($/hour)</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>average number of working days in a year</td>
</tr>
<tr>
<td>$h$</td>
<td>agency budget cost limit over the planning horizon</td>
</tr>
<tr>
<td>$\psi(\cdot)$</td>
<td>simulation that evaluates the travel times of all vehicles</td>
</tr>
<tr>
<td>$\pi$</td>
<td>monetary equivalence factor for user cost</td>
</tr>
<tr>
<td>$\theta$</td>
<td>incident characteristics parameter (duration and severity)</td>
</tr>
</tbody>
</table>
Given: 
\[ T_s, T_e, t^e_{i,j,k} \]

Objective function:
\[
\min_y B = \sum_{n \in N} (c_n + o_n) y_n + \pi \cdot \varphi \cdot d \cdot \kappa \cdot \left\{ E \left[ \sum_{v \in V} t_v \right] - T \right\} 
\]  \hfill (5)

Subject to:
\[
t_v = \psi (r^e_{i,j,k}, Q, \theta, Y) \quad \forall v \in V 
\]  \hfill (6)
\[
\sum_{n \in N} (c_n + o_n) y_n \leq h 
\]  \hfill (7)
\[
y_n = 0 \quad \text{or} \quad 1 
\]  \hfill (8)

The objective function (5) is composed of agency cost \( \sum_{n \in N} (c_n + o_n) y_n \) and user cost \( \pi \cdot \varphi \cdot d \cdot \kappa \cdot \left\{ E \left[ \sum_{v \in V} t_v \right] - T \right\} \). The term \( \sum_{n \in N} (c_n + o_n) y_n \) is the total agency cost for the deployed DMS over the planning horizon. This represents the budget-oriented decision without considering the unfolding incident and diversion and resultant user costs. The term \( E \left[ \sum_{v \in V} t_v \right] - T \) represents the additional average total user travel time due to the stochastic incident and DMS diversion compared to the no-incident case. The parameters \( \pi, \varphi, d, \kappa \) are used to convert the user cost from the time unit to the equivalent monetary cost.

Furthermore, the total system user travel time under incident situation \( \sum_{v \in V} t_v \) is the sum of individual vehicle’s travel time \( t_v = \psi (r^e_{i,j,k}, Q, \theta, Y) \). \( t_v \) has to be evaluated by the simulation model as individual vehicle’s travel time is subject to complex dynamic interactions with other vehicles, stochastic incident location \( Q \) and characteristic (duration and time) \( \theta \), and number of active DMS \( Y \). The budget constraint (7) states that the total required agency cost is subject to the budget limit \( h \). Constraints (8) indicate that if the binary decision variable \( y_n \) takes a value 1, then the candidate DMS location \( n \) is selected.

4. Solution procedure

The simulation-based dynamic traffic assignment (DTA) model DYNASMART-P with DMS diversion capability, is modified and embedded into a Tabu search heuristic to solve the SODMSL problem. A schematic view of the solution procedure is shown in Fig. 2. Before discussing the solution procedure, a general overview of the Tabu search heuristic is presented. The solution algorithm of DYNASMART-P has been sufficiently described in the literature (Mahmassani et al., 1993; Peeta and Mahmassani, 1995; Mahmassani et al., 2000), and therefore it will not be discussed herein.

A typical Tabu search heuristic consists of the forbidding-freeing strategy, move selection, short-term strategy, and stopping criterion (Glover and Laguna, 1993). The forbidding strategy constrains the search by classifying certain moves as forbidden (Tabu) based on Tabu conditions, which are identified by the attributes (i.e. DMS locations) of a move. Due to the possibility of cycling (revisiting a visited move) a Tabu list is maintained to ensure a partial range of solution attributes will not be revisited within a certain pre-defined number of iterations (given by the Tabu tenure). The Tabu list is maintained in a first-in first-out (FIFO) manner. Whenever a new Tabu move is added to the end of the list, the head move is pushed out and becomes a non-Tabu move.

The move selection determines a trial move and then makes it a candidate move if it is not a Tabu move; otherwise, it regenerates a new trial move. A trial move involves a drop move and an add move. The drop move determines which candidate is to be dropped from the current solution set, and the add move determines which of all other candidates is to be added. In TABU-DTA, the drop move is based on a uniform probability distribution, and the add move utilizes information obtained from prior experiments, and knowledge accumulated over iterations. The prior experiments involve using TABU-DTA to evaluate the total user travel time of each candidate location, namely, fixing the location and draw random incidents and activate corresponding DMS for diversion. The locations are then ranked according to the averaged total user travel time over
incident realizations. The rankings of the candidate solutions from using one DMS are referred to as the initial solutions for the TABU-DTA algorithm. The short-term strategy controls the interaction between the forbidding and freeing strategies. It includes an aspiration strategy that ignores Tabu restrictions and a selection strategy that chooses trial solutions based on move selection strategy. The stopping criterion limits the algorithm to a specified maximum number of iterations.

The probability of selecting a candidate location \( n \in N \), \( P^k_n \), referred to as an add move, is adaptive to that candidate location’s performance in previous iterations. This is achieved by defining an Elite Group (EG) \( E_k = \{e_1,\ldots,e_{\varepsilon}\} \) at iteration \( k \), which is a set of best \( \varepsilon \) solutions found over iterations up to iteration \( k \), where \( e_i \) is the set of locations comprising a particular solution.

More specifically, the add move probability for choosing location \( n \) at iteration \( k \), can be expressed as in Eq. (9), which indicates that the add move probability is initialized using a probabilistic selection strategy based on the following logit-formulation when the iteration number is less than \( \varepsilon \). For iteration number greater than \( \varepsilon \), \( P^k_i \) takes the linear combination of \( P^{k-1}_i \) and \( q^k_i \) with the discount factor/weight \( 1/(1+k) \) over iterations. This adaptive adjustment of the add move probability allows \( P^k_i \) to change with higher magnitude in the early round of iterations and then gradually settle down to a stable range.

Fig. 2. TABU-DTA solution procedure.
\[ P_n^k = \begin{cases} \sum_{j \in N} e^{-a g_j}, & \forall k \leq \varepsilon \\ \left( 1 - \frac{1}{1+k} \right) p_n^{k-1} + \left( \frac{1}{1+k} \right) q_n^k, & \forall k > \varepsilon \end{cases} \]  

where

\[ q_n^k = \frac{f_n}{\sum_{i=1}^e |e_i|}, |e_i| \]

is the size (number of DMS sites) of each solution in the EG,

\[ f_n : \text{frequency of candidate location } n \text{ appears in the EG}, \]

\[ k : \text{iteration number}, \]

\[ \varepsilon : \text{size of EG}, \]

\[ g_j : \text{average user travel time for DMS node } j \text{ obtained from the 1-DMS scenario}, \]

\[ a : \text{scaling parameter}, \]

\[ N : \text{set of candidate DMS nodes}. \]

The appearance frequency of candidate location \( n \) (i.e. \( f_n \)) in the EG is further illustrated in Fig. 3. In this example, The EG consists of five best solutions as of iteration \( k \). Each candidate solution is a vector consisting of different locations. For example, the “Best solution 1” indicates that candidate location configuration (1, 4, 7, 10) is one of the 5 best solutions defined in the EG. Moreover, \( f_n \), the frequency of candidate location \( n \) appears in the EG is calculated by taking the total counts of location \( i \) in the EG divided by the total count in the group. For example, location 4 appears three times in the group and the total location count in the group is 18; therefore \( n_4 = 3/18 = 0.167. \)

The following presents the steps of the TABU-DTA solution procedure.

1. Determine the solution space by identifying all feasible DMS locations. A feasible DMS location is defined as the upstream node of a highway link with an off-ramp in its immediate downstream. Set iteration counter \( k = 1 \).
2. Find a new candidate solution by dropping a location from the current solution and add one based on Eq. (9).
3. Generate a random incident realization by drawing a random number from the uniform distribution, \( U(0,1) \), and map it to the corresponding cumulative distribution, which is constructed from the probability mass function based on Eq. (2) (see Section 2.1). Identify the set of active DMS nodes \( N_A \) whose activation segment contains the incident.
4. Perform traffic simulation for all vehicles \( v \in V \).
   a. Initial path generation: by default, the initial path set \( K_{i,j}^{\text{ini}} \) is determined \textit{a priori} based on the UE principle. If the ATIS scenario applies, the \( K_{i,j}^{\text{ini}} \) for ATIS-accessing vehicles are updated periodically according to unfolding traffic.
   b. Update of initial paths for ATIS-accessing vehicles (ATIS scenario only).
c. ATIS access (ATIS scenario only): Monte Carlo approach is employed to determine whether the generated vehicles access the ATIS prior to the trip departure. User-specified ATIS compliance rate is applied.
d. Initial path assignment: non-ATIS-accessing vehicles will be given a priori UE paths based on its origin, destination and departure time and ATIS-accessing vehicles will be given initial paths that are periodically updated based on the latest traffic condition.
e. DMS activation: activate all DMS $n \in N_A$ at simulation time steps $t \in [T_s, T_e]$.
f. DMS diversion: when a vehicle $v \in D$ is identified in the simulation, calculate K-shortest paths and assign the vehicle to a randomly selected path from the K-path choice set. The vehicle $v \in D$ follows the newly assigned path until it reaches its destination. All vehicles $v \in ND$ follow the original path $k \in K_{ij}^{im}$ without diversion. When the simulation run is finished, compute the MoE.

5. Update the Elite Group if this candidate solution’s MoE is among the best $\varepsilon$ solutions found so far.
6. Repeat from step 3 for a pre-defined number of incident realizations.
7. Update the current solution and Tabu list.
8. Repeat from step 2 until the specified maximum iteration is reached, or until the convergence criterion is met.

5. Case study on DMS location configuration design and ATIS interactions

5.1. Scenario design

To demonstrate the applicability of the proposed methodology, the proposed model and solution algorithm is tested on the Fort-Worth, Texas network to determine an optimal DMS location configuration. A diagram of the network is shown in Fig. 4. It consists of 13 zones, 178 nodes, and 441 links. The freeway in the network represents a segment of the Interstate Highway 35W, between Interstate Highway 20 and Interstate Highway 30, which runs through the Fort-Worth area. The network is constructed with 64 signalized intersections, all of which are modeled as actuated controls. The non-signalized intersections are modeled with stop controls. Altogether, there are 13 possible locations along the freeway section to install DMS. These 13 locations are referred to as candidate locations (labeled in Fig. 4).

Table 1 lists general cost related inputs as well as those which pertain to “DMS only” and “DMS+ATIS” scenarios. In the “DMS only” scenario, no ATIS service exists. Tripmakers are not aware of the incident occurrence until they arrive at the incident site. The “DMS+ATIS” scenario incorporates a varying degree of ATIS information compliance. All of the specified model inputs are based on values often used in the literature or values given by practitioners; they are provided here for illustration purposes only. In all the experiments conducted, the severity and duration of incidents are kept constant. The severity is assumed to reduce 80% of the link capacity, and the duration is assumed to last for 45 min starting from simulation minute 4 to minute 50. Incident location is the only random variable in the experiment. During each realization, only a single incident is generated. The DMS response rate is assumed to be 15%. The demand is equivalent to approximately 12,000 vehicles being loaded onto the network over a 2-h simulation period. The traffic pattern follows that of a morning peak in which traffic moves from the southeast towards the northwest region. The number of working days in a year is assumed to be 200 and the incident occurrence rate is 0.5/day. Only situations in which zero or one incident occurred during the simulation period are considered in this case because the cumulative probability of both event accounts for more than 0.9 based on the occurrence rate of 0.5/day.

Four different ATIS compliance rates (0%, 10%, 30% and 100%) are considered. The 10% scenario is later used for comparing the “DMS only” versus “DMS+ATIS” scenarios; other market share scenarios are used for DMS-ATIS inter-dependence analysis. It should be noted that the high compliance rates such as 30% and 100% are not likely in real-life, but they are incorporated in this analysis to give a broader spectrum of the compensatory effect between DMS and ATIS. These scenarios are used for benchmarking purposes only.

The hourly wage rate is assumed to be 10 dollars an hour. The length of the DMS activation segments is assumed to be two miles. The total budget is assumed to be three million dollars over the 10-year planning horizon. For DMS related inputs, the deployment cost is assumed to be two hundred thousand dollars per DMS unit, and the operating and maintenance cost is assumed to be 40 thousand dollars per
DMS per year. Note that the economy of scale associated with installing more number of DMS is not considered in this study because we did not find a consistent and significant volume discount practice in the U.S. The deployment cost (including mainly the processing, integration and dissemination of existing traffic detection data) for ATIS is assumed to be 250 thousand dollars and the operating and maintenance cost is assumed to be 80 thousand dollars per year (Carter et al., 2000). Note that the case study assumes that the traffic surveillance system is already in place. Therefore, the cost of deploying the traffic detection system for the operation of DMS or ATIS is excluded from the deployment costs of DMS or ATIS. All of the above parameters are assumed to remain unchanged during the planning horizon.

The user cost is defined as the total extra costs incurred by the users due to the incidents compared to the no-incident situation. It is calculated by taking the difference in total travel times between any deployment scenario (with incident) to the baseline scenario (no incident) times total number of working days with incident and convert to monetary value by the hourly wage rate and the monetary equivalence factor. The Net Present Value (NPV) method with discount rate at 3% is used to convert both deployment and user cost that occur in each planning year to the present value in order to have a common basis for comparison. For simplification purpose, the hourly wage rate and user population are assumed to remain unchanged over the planning horizon.

Fig. 4. Fort-Worth network.
The value of the monetary equivalence factor is set to be 0.5 as it was recommended that travel time savings on surface modes be valued at 50% of the wage rate for local personal travel (Kruesi, 1997).

The two key parameters in the Tabu search heuristic, Tabu tenure and maximum number of iterations, are set to be 30 and 100, respectively. At each Tabu step, 30 incident realizations are generated. As discussed in Section 3, the incident occurrence is assumed to follow the spatial Poisson process; that is, every freeway link has a likelihood of having an incident on it proportional to its lane-mile. Subsequently, a cumulative spatial probability mass function over the links can be established. For each incident location realization, a random number from the uniform distribution \( U(0,1) \) is drawn and mapped to the cumulative distribution function to determine which link will have the incident.

### 5.2. Case study results

The experiment results for the two studied scenarios – “DMS only” and “DMS+ATIS” – are presented in Figs. 5 and 6, respectively. The costs shown in both figures are the NPV of all costs over the planning horizon. In the “DMS only” scenario, the agency cost (e.g. \( \sum_{n \in N} (c_n + o_n)y_n \)) increases approximately linearly with increasing number of DMS – from $0 at “no-DMS” to $2.4 million at “5-DMS”. The user cost (e.g. \( \phi \cdot d \cdot \kappa \cdot (E[\sum_{v \in V} r_v] - T) \)) in the “no-DMS” case is about $13 million. The user cost steadily decreases to $8.9 million (35% improvement over the no-DMS case) at “4-DMS” and $8.8 million (36% improvement over the no-DMS case) at “5-DMS”. The total cost, combining agency and factored user costs, decreases from $6.9 million at “no-DMS” to an optimal $6.0 million (12% improvement) at “4-DMS” case. The reason why the result for the “5-DMS” case is inferior to the result of the “4-DMS” case is because the marginal improvement in the user cost significantly decreases when the number of DMS increases from 4 to 5; the user cost improvement therefore does not compensate the increased agency costs. Although the curve of the total cost appears to relatively flat, one can still clearly discern that the 2-DMS case is where beyond which point increasing number of DMS does not necessarily translate to additional benefits. However, one would expect that if higher

### Table 1

<table>
<thead>
<tr>
<th>Case study scenarios and model inputs</th>
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<td>DMS only</td>
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<td><strong>General model inputs</strong></td>
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<td>Monetary equivalence factor (( \pi ))</td>
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<td>Deployment cost (( c_n ))</td>
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<tr>
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<td>Deployment cost (( c_n ))</td>
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<td>O&amp;M cost (( o_n ))</td>
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hourly wage rate was used ($10/hr was used for this case study), the benefit of adding more DMS may become more distinct.

The results for the “DMS + ATIS” scenario, shown in Fig. 6, reveal that when ATIS is in place, deploying 2-DMS is the optimal strategy from a total cost perspective. The total cost ($5.5 million) is lower than that of the optimal solution in “DMS only” scenario ($6M). The agency and user costs in the two scenarios also exhibit significant distinction. In the “DMS only” scenario, the minimal user cost is $8.8 million at the 5-DMS scenario. In the “DMS + ATIS” scenario, the optimal user cost is significantly lower ($7.3 million). For any given number of DMS, the agency cost is higher in the “DMS+ATIS” scenario than that in the “DMS only” scenario because of additional resources needed for maintaining the ATIS. Note that the user cost decreases quickly in the case in which 1- or 2-DMS are deployed together with ATIS; however, the marginal improvement significantly diminishes when the number of DMS is greater than two. A possible reason for the quick level-off of marginal DMS benefit, as discussed in Section 4, is that those who receive incident information via the ATIS may decide to select different routes/departure times to avoid the incident which may cause a decrease in traffic arriving at the incident site. In such instances, additional number of DMS does not considerably improve the user cost.

Additional simulation experiments with different ATIS market shares (in addition to the 10% case) were also conducted. The results suggest a certain compensatory effect between the DMS and ATIS service. In Fig. 7, the average user travel time under different number of DMS and ATIS scenarios are presented. The four curves indicate the average user travel time under four ATIS compliance scenarios (0%, 10%, 30%, and 100%). Given each number of DMS, the user travel time generally decreases with increasing ATIS compliance rate (except from 30% to 100%). Given an ATIS service compliance rate, adding DMS also improves system performance. This suggest that DMS and ATIS compensate each other in terms of traffic management.
benefit and that combining ATIS services with DMS deployment yields better system performance than deploying these systems individually. The added benefit of the combined DMS and ATIS strategy comes from different temporal and spatial traffic dispersion that the two strategies jointly produce to mitigate the impact of an incident. The ATIS information helps users to adjust route choice or departure times at the beginning of their trips in response to the incident, while DMS help users to make local en-route route adjustment to avoid the incident.

Fig. 7 also demonstrates the undesirable effect of ATIS information saturation. Generally speaking, at a very low market share, increasing ATIS market share significantly improves system performance. However, when all the users access pre-trip information, the user cost worsens. In the tested scenario, the travel time with 100% ATIS compliance is higher than that with 30% compliance. This phenomenon indicates that when all users access pre-trip information, the collective route or departure time choice behaviors make the system become less efficient than if only a fraction of users take advantage of the information. Similar findings were first reported in Mahmassani et al. (1993).

It can also be observed that the two information strategies nullify the marginal benefits of one another. Based on Eqs. (3) and (4), compensatory effect between DMS and ATIS can be analyzed as follows. In the case in which no ATIS service exists, the average user travel time with “5-DMS” is 30.4 min, equivalent to $B(d = 5|\lambda = 0) = 8.6\%$ improvement over the 33.3 min of the “no-DMS” case. With ATIS introduced at 30% market share, the marginal system improvement drops to $B(d = 5|\lambda = 0.3) = 2.7\%$ under the same DMS scenario. In other words, with ATIS the benefit of increasing the number DMS is not as significant as if no ATIS is deployed. Similarly, with DMS deployed, the increasing market share of ATIS is not as beneficial as if no-DMS is deployed. As shown, when no-DMS is deployed, the average user travel time due to compliance of ATIS (from 0% to 30%) is reduced from 33.1 min to 29.5 min, equivalent to a $B(\lambda = 0.3|d = 0) = 10.8\%$ improvement. However, with five DMS deployed, the marginal improvement is reduced to $B(\lambda = 0.3|d = 5) = 3.0\%$ under the same ATIS market share scenario.

Such results indicate that when evaluating the benefit of Intelligent Transportation Systems (ITS) technologies or components one needs to be aware of the inter-dependency between various technologies/systems and their compensatory/substitution effect. As illustrated earlier, if DMS and ATIS are planned separately without considering the existence of other ITS information strategies, one would estimate improvement for respective systems to be 8.6% and 10.8%, respectively. However, the actual improvement appears to be 2.7% and 3.0% respectively given the coexistence of both systems. Moreover, if the DMS is planned separately from the ATIS service, the investment decision is to deploy 4-DMS plus the ATIS. The agency cost is $2.5M, which is higher than that of the optimal combined build-out scenario (2-DMS plus the ATIS) at $1.8M. The combined cost of

![Fig. 7. Compensatory effect between DMS and ATIS.](image-url)
the former strategy is also higher than the latter one. This indicates a higher cost with less benefit, which suggests ineffective execution of the fund.

In addition to affecting the marginal benefits of DMS, ATIS also affects the optimal locations of DMS. The “DMS only” and “DMS + ATIS” scenarios generate different optimal locations. In the “DMS only” scenario, the optimal configuration has four DMS with two on each direction of the Interstate Highway 35W. As seen in Fig. 8, two out of the four sites are located at the north side of the network. For the southbound direction, location 1 and 12 are associated with two consecutive off-ramps; the other two (10 and 3) in the northbound direction are relatively further apart. For the “DMS + ATIS” scenario (with 10% ATIS compliance rate), both DMS are located at the southern part of the freeway. One of the locations (location 9) is close to the location 10 in the “DMS only” scenario. However, location 8 is quite far from those located in the southbound freeway in the “DMS only” scenario. These results suggest the importance of planning and designing ITS information provision components/strategies in a unified manner, so that the inter-relationship of the resulting system performance between strategies is properly captured.

To better understand how ATIS may affect the optimal locations of DMS, another experiment was performed to compare the optimal 4-DMS solution with “DMS only” against “DMS + ATIS”. As shown in Fig. 9, the optimal DMS configurations between the two cases are not alike, and this can only be attributed to the presence of ATIS. Only two sites (10 and 12) were included in both optimal solutions. The “DMS only”
solution yields two DMS on each side of IH 35W, but the “DMS + ATIS” solution indicates that more DMS should be installed on the southbound side.

6. Conclusions

The strategic decision of effectively deploying a number of DMS is of key interest from both the long-term planning and short-term operation perspectives. To address this issue, this paper proposes a methodology for finding the optimal number and location of DMS to deploy. Optimality is defined in the sense of minimizing the deployment, operating and maintenance cost, and long run expectation of incident-incurred user cost under stochastically occurring incident situations. The proposed framework is formulated as a stochastic integer program with recourse. The specially designed TABU-type solution algorithm is implemented and applied using the Fort-Worth, Texas network.

This paper also addresses the effect the inter-relationship between DMS and ATIS information provision has on system performance. Experimental results indicate a strong inter-relationship between the two strategies, primarily the diminishing rate of marginal benefit in one strategy due to the existence of the counterpart strategy. From the system management perspective, it is found that designing and deploying DMS and ATIS jointly is more cost-effective and efficient than sequential build-out of the two.

Fig. 9. Optimal locations for “DMS only” (left) and “DMS+ATIS” (right), given four.
This study underscores the complex dynamics of traffic flow and tripmakers’ travel behavior in the presence of real-time information, especially in regard to DMS diversions. Important factors affecting the solution include demand, network structure, DMS response rate, and incident characteristics. This study can be extended by considering randomness in incident severity and duration, and by using more realistic incident occurrence characteristics (e.g. assume incident occurrence rate to be proportional to traffic volumes instead of link length), as well as modeling situations with multiple incidents. Alternative behavioral rules that correspond to user adaptation and choice under imperfect information and bounded search domains could be incorporated to the present study to provide further insight.

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