DEVELOPMENT OF AN EMISSION-BASED SELECTION ALGORITHM TO OPTIMIZE VARIABLE MESSAGE SIGN LOCATIONS

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<tr><td colspan="4">16. Abstract
This project devised an optimization method to site variable message signs (VMSs) for traffic incident management. The optimization objective is to maximize the economic utility of each VMS, considering both the monetary value of time and value of emissions. The method includes an integrated traffic and emissions simulation module and an optimization module that stochastically sample from real-world incident data. The method was applied to El Paso, Texas, as a case study. The case study demonstrated convergence of the optimization process, arriving at a stable set of optimal sites given various input assumptions. The optimally sited VMSs showed favorable societal return on investment in congestion relief and emissions reduction.</td></tr>
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Executive Summary

This project devised an optimization method to site variable message signs (VMSs) for traffic incident management. The optimization objective is to maximize the economic utility of each VMS, considering both the monetary value of time and value of emissions. The method includes an integrated traffic and emissions simulation module and an optimization module that stochastically sample from real-world incident data. The method was applied to El Paso, Texas, as a case study. The case study demonstrated convergence of the optimization process, arriving at a stable set of optimal sites given various input assumptions. The optimally sited VMSs showed favorable societal return on investment in congestion relief and emissions reduction. Ten optimally sited VMSs can save around $1.3 million a year in time savings and emissions reduction through diverting traffic after roadway crashes, assuming a medium monetary value of time and emissions.

The optimization methodology is implemented as an automated modeling pipeline referred to as TEMPO-Safety. The framework consists of four tools—the crash road matching algorithm, the stochastic crash generation algorithm, the potential VMS location algorithm, and the optimal VMS locator. This suite of tools allows a user to draw from a roadway crash database, in this case managed by the Texas Department of Transportation; assemble a stochastic representation of crash likelihood for each roadway link; identify plausible locations of VMSs; and select optimal VMS locations based on crash likelihood and associated congestion and emissions impacts.

The methodology and resulting TEMPO-Safety suite can be applied to other metropolitan areas, especially within Texas considering the consistency in the roadway crash database. The optimization methodology can be further extended to other infrastructure siting decisions.

Acknowledgments

This research leveraged an ongoing project of the Texas A&M Transportation Institute sponsored by the ExxonMobil Research and Engineering Company titled Development of an Integrated Transportation and Emissions Modeling Platform for Optimization (TEMPO).

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Background and Introduction

CARTEEH QUICK FACTS

CARTEEH is a Tier 1 University Transportation Center, funded by the U.S. Department of Transportation's Office of the Secretary for Research and Technology.

Variable message signs (VMSs) are a key component of intelligent transportation system (ITS) technologies and, more specifically, a real-time traveler information tool. Estimated travel times on freeways, corridor congestion, construction and maintenance schedules, special event instructions, and incident notifications can be conveyed through VMSs. Previous studies of VMSs mostly focused on the impact of VMSs on network performance (Chatterjee et al., 2002; Lam and Chan, 1996; Shi et al., 2009). Few studies have been conducted to associate VMSs with environmental effects, specifically emissions reduction (Hoye et al., 2011). A 2006 study estimated a 9.2 percent reduction in fuel consumption and an 8.7 percent reduction in CO_2 after implementing a VMS route strategy during incidents (Dia and Cottman, 2006). Later, a 2017 study found traffic management tools and VMS guidance can reduce black carbon emission by up to 3% (Mascia et al., 2017). Also, the highest performance gain and emissions savings occur when VMS locations are wisely selected (Fan et al., 2018; Shang and Huang, 2007). Thus, the allocation of the VMS is the key to an optimized network.

While most traffic agencies use engineering judgment to locate VMSs in the network, some research has been conducted on the optimization of VMS locations to maintain various objectives (maximizing information/guidance or minimizing delay). Generally, three levels of optimization can be considered regarding VMS locations:

1. **Optimal selection of the locations to install a new VMS:** Most studies focus on finding optimal locations to place within a network without VMSs (Abbas and McCoy, 1999; Chiu and Huynh, 2007; Chiu et al., 2001; Fan et al., 2018; Gan et al., 2011; Shang and Huang, 2007; Xiangjun and Honghui, 2011; Zhang and Gao, 2012). These studies used a theoretical or simulation-based model to find the VMS locations that maximize benefits (guidance) or minimize network delay.
2. **Optimal selection of the existing VMS board to present received information:** To find the optimal VMS locations to provide guidance, we may either a) evaluate the individual impacts of existing VMS boards to find the one with the most guidance benefits, or b) optimize VMS locations considering a network with no VMS and map it to the real-world VMS system. A 2017 study estimated the black carbon emission impact for a whole VMS system in the network (Mascia et al., 2017). A 2011 study implemented the second path and optimized VMS locations for a perfect network and mapped it to the real construction plan for VMS (Xiangjun and Honghui, 2011).
3. **Optimal selection of a set of VMS boards:** All previously mentioned studies consider adding a new set of VMS boards or evaluating the impacts of the existing VMS boards. However, most cities have a set of exiting VMS boards functioning in the network. Therefore, a real optimal set should integrate these two sets and find the new locations for VMS boards while considering the impact of the existing VMS boards in the network. This is the main research gap in optimizing VMS locations.

Other than the aforementioned lack of research in the third level of VMS location optimization, previous studies have some other gaps that can be better addressed for the future:

- The objective function of the previous optimization models was either minimizing travel time and delay or maximizing guidance information (Gan et al., 2011; Si et al., 2017; Xiangjun and Honghui, 2011; Zhang and Gao, 2012). No studies have assessed the emissions savings from the proposed optimization models.
- Previous case studies usually assumed crash events for VMS location optimization. Few studies obtained real-world historical recurring congestion data (Abbas and McCoy, 1999; Chiu and Huynh, 2007; Chiu et al., 2001; Si et al., 2017; Zhang and Gao, 2012).
- Previous studies implemented the optimization algorithm on a small region or corridor, rather than an actual network (Chiu and Huynh, 2007; Chiu et al., 2001; Fan et al., 2018; Gan et al., 2011; Si et al., 2017; Xiangjun and Honghui, 2011; Zhang and Gao, 2012).

- Previous studies suggested ideally optimal VMS locations, rather than a set of optimal locations based on the existing VMS boards (Fan et al., 2018; Gan et al., 2011; Xiangjun and Honghui, 2011; Zhang and Gao, 2012).

Therefore, this study has devised a bi-level emission-based algorithm to select the optimal VMS locations within a network. The lower level uses multiple sources of real incident data and searches for the optimal locations from the potential VMS locations. The next level conducts a delay- and emission-based utility assessment for the installation of a new VMS board at an optimal location and finds a proposed set of VMS locations. The benefit of installing a new VMS board is emissions savings though the agency may have to pay the purchase cost and maintenance fee. Table 1 shows how this proposed methodology addresses the research gaps and CARTEEH priority areas.

Table 1. Key Research Gaps and Addressed Solutions

Key Aspect	Current Research Gap	Solution Provided in This Study	Addressed Priority Area
1	No assessment of emissions savings or monetary cost	The optimization is based on the emissions savings and VMS board cost	Impact assessment
2	No real-world data incorporated in the optimization algorithm	Real-world incident data are obtained	Data integration
3	No actual or big-scale networks	The algorithm is built on existing optimization models to work for any region scale and is applied to the El Paso network as a case study	Modeling studies
4	No set of optimal VMS locations	The second level of optimization searches for the set of optimal VMS locations among existing and ideal board locations	Modeling studies

Methodology

The current study proposed and developed a transferable optimization platform, termed TEMPO-Safety, to search for the VMS board locations. TEMPO-Safety integrated the Transportation and Emissions Modeling Platform for Optimization (TEMPO) into a new pipeline for maximizing congestion reduction and emissions reduction from the installation of VMS boards at proposed locations using historical incident data. Further, the TEMPO-Safety pipeline was applied to the El Paso network. Therefore, the following goals of the study were achieved:

1. Crash warning framework development and data integration platform.
2. Stochastic emissions reduction calculation for crash events.
3. Optimal selection of the locations using congestion reduction and emissions reduction.
4. A large-scale case study for El Paso.

Figure 1 illustrates the TEMPO-Safety framework and integrated databases and algorithms. The following sections introduce each element of the framework, including the data structure and inputs, TEMPO, and algorithms for crash analysis and optimization.

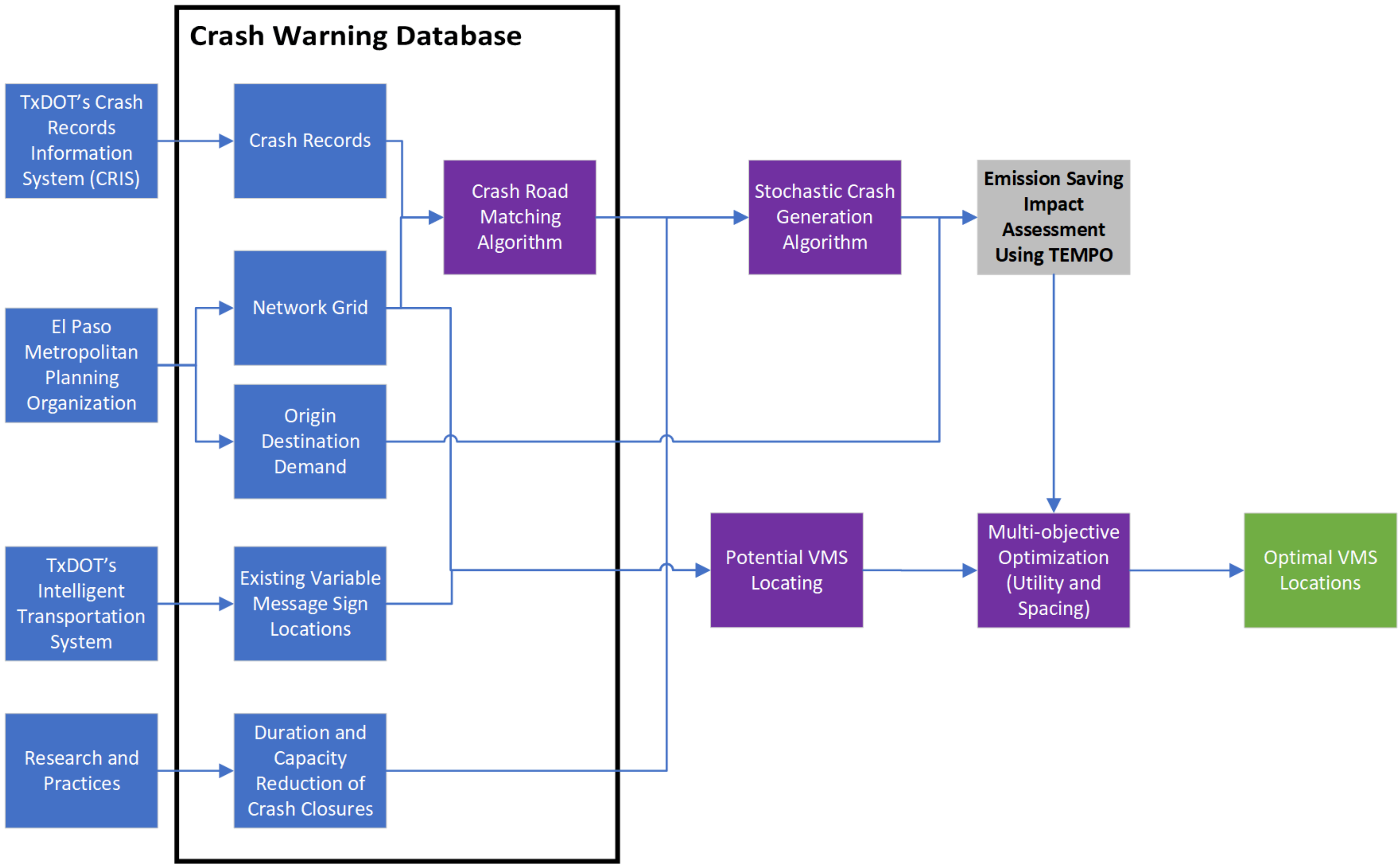

Figure 1. TEMPO-Safety framework.

Crash Warning Database

The crash warning database in the TEMPO-Safety framework integrates five datasets from four different official sources for the El Paso network. The datasets are:

- Dataset 1: Crash Records.
- Dataset 2: Network Grid.
- Dataset 3: Origin-Destination Demand.
- Dataset 4: Existing Variable Message Sign Locations.
- Dataset 5: Duration and Capacity Reduction of Road Closures.

Dataset 1: Crash Records

Historical crash records may be obtained from police officers' crash reports. These reports detail the crash location, time, and severity. El Paso crash events were obtained from the Texas Department of Transportation (TxDOT) Crash Record Information System from 2014 to 2018, for a total of 109,145 crashes. The number of reportable crashes (on-road crashes with property damage of more than $1000) with available coordinates was 82,819. Figure 2 shows the distribution of these crashes based on crash severity over the years.

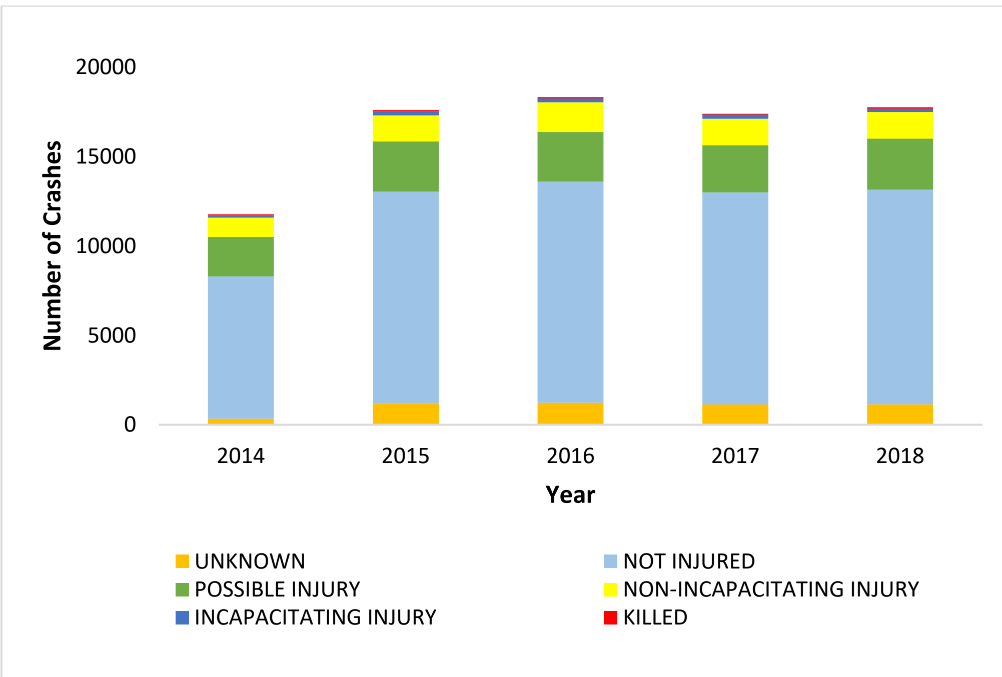

Figure 2. Distribution of crash severity over years.

Dataset 2: Network Grid

Texas A&M Transportation Institute researchers configured a mesoscopic dynamic traffic assignment model for the current El Paso network (Shelton and Nava, 2009) using El Paso's metropolitan planning organization (MPO) roadway network configuration and land use. The El Paso network configuration includes the roadway system's geometry and link specifications, especially the street names and lengths. The roadway configuration was iteratively quality assured and updated during previous studies (Shelton et al., 2014; Vadali et al., 2015) and the current study to represent the most accurate and updated roadways, traffic movements, and traffic flow. The latest version of the El Paso network includes 836 traffic analysis zones, 5667 nodes, and 9865 roadway links. Detailed characteristics of each roadway, including length and operational classification, are incorporated into the crash warning database (Figure 3).

Dataset 3: Origin-Destination Demand

Travel demand data for the El Paso region were developed using the El Paso MPO regional travel demand models. The origin-destination demand data were a time-series matrix of the number of trips between every two zones for each vehicle type and aggregated for each hour of the day. The total number of 24-hour trips in the El Paso region was 2,491,515 trips.

Dataset 4: Existing Variable Message Sign Locations

The list of operational VMS locations was retrieved from TxDOT's ITS inventory. The coordinates for each location were quality assured using the most recent El Paso map and projected into the corresponding roadway in the El Paso network grid. In some cases, a single VMS was viewable from more than one roadway and was considered for projection to all relative roadways. The El Paso road system had a total of 80 VMSs and was included in the crash warning database, as illustrated in Figure 3.

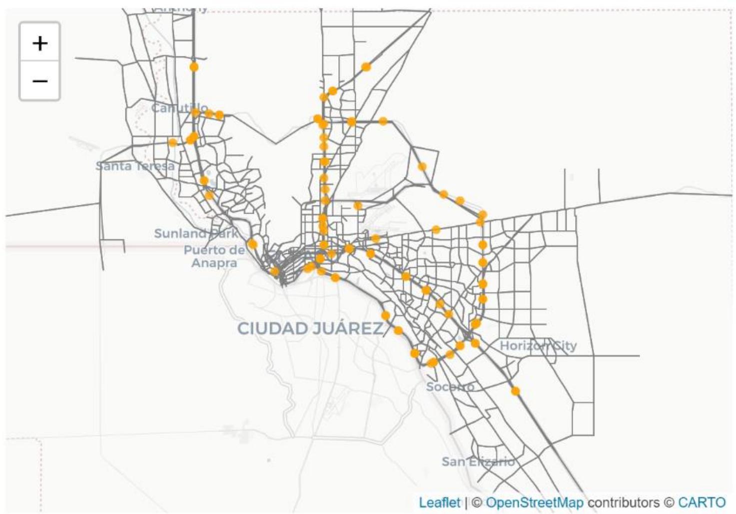

Figure 3. Existing VMS locations in the El Paso region.

Dataset 5: Duration and Capacity Reduction of Road Closures

Crash events may lead to road closures and capacity reduction for an incident clearance duration and beyond. The clearance duration and capacity reduction have been the focus of various studies (Brown et al., 2020; Gopinath et al., 2016; Haule et al., 2019; Ji et al., 2014). The crash warning database used previous literature (Li et al., 2017; Won et al., 2018), real-world crash reports, and current practices in the El Paso region to develop the clearance duration and capacity reduction of crashes based on their severity. Table 2 shows the clearance duration and capacity reduction after the crash event for each class of crash severity.

Table 2. Clearance Duration and Capacity Reduction of Crash Severity Levels

Crash Severity	Clearance Duration	Capacity Reduction
Fatal	120	0.75
Incapacitating	90	0.75
Non-incapacitating	75	0.5
Possible injury	60	0.5
Not injured	45	0.25
Unknown	30	0.25

Traffic and Emissions Modeling

Robust analysis of the emissions impacts of crashes requires rapid traffic and emissions simulation runs. Crash days were drawn from the crash warning database to establish a representative sample of crash occurrences.

Researchers then ran TEMPO to simulate the traffic impact and the resulting emissions impact. TEMPO is a cloud-based modeling platform for integrating and automating a suite of transportation, energy, and emissions models that provides sound evidence for optimized infrastructure decision-making to regulators and policymakers (Sharifi et al., 2021).

In TEMPO, traffic patterns are simulated with a mesoscopic dynamic traffic assignment (DTA) model. The DTA model analyzes the movement of individual vehicles (as in microscopic models) while using macroscopic traffic flow theories without complicated vehicle interactions (Chiu et al., 2011). Vehicle emissions are modeled with MOVES-Matrix (Liu et al., 2019). In addition to the modeling tools, TEMPO has the essential database for each step of the modeling. Traffic assignment and emissions estimation evaluation depend on many other factors than the travel demand and vehicle activity in the system, including the traffic flow model, age distribution of the vehicles, and meteorological metrics.

The main strength of using the TEMPO pipeline in the current study compared to the previous approaches is the efficiency in running time to assess the emissions impacts of generated crash scenarios. TEMPO can estimate the traffic and emissions impacts of 50 crash scenarios in an acceptable time frame and overcome the disconnection between traffic activity and emissions impact models caused by resolution mismatch and processing of resources (Sharifi et al., 2021).

TEMPO-Safety Tools

The current study developed the following four tools, referred to as the TEMPO-Safety framework, to adapt TEMPO for assessing the impacts of crash warning systems such as VMS:

- Tool 1: Crash Road Matching Algorithm.
- Tool 2: Stochastic Crash Generation Algorithm.
- Tool 3: Potential Variable Message Sign Location Algorithm.
- Tool 4: Optimal Variable Message Sign Locator.

Tool 1: Crash Road Matching Algorithm

The crash road matching tool was developed and implemented to project each crash record to the correct road segment in the network. The spatial matching algorithm is a complicated problem, and the current study diagnosed multiple issues and treatments to solve them in the development of the matching algorithm:

- The crash coordinates may correspond to any place in the width of the street. However, the existing mesoscopic network configuration (Dataset 2: Network Grid) uses lines to represent roadway segments.
  - Treatment 1: Creating a road width-wide buffer around network lines.
  - Treatment 2: Snapping crashes to the road segments based on buffering.
- At intersections or interchanges, there are some overlapping streets.
  - Treatment 3: Using road names for matching.
- The road names may not match precisely between two sources (state road names and spellings).
  - Treatment 4: Scoring the matches.

Researchers used these treatments and both distance and label features to systematically find and rank the most accurate road segments for each crash record. The algorithm finds the 10 closest roads to each crash record and ranks them based on their distance and label matching. Therefore, a list of potentially matching roads with their probability is generated for each crash event.

Tool 2: Stochastic Crash Generation Algorithm

The crash-generating algorithm uses the crash warning database and automates the stochastic crash scenario generation for the daily congestion and emissions impact assessment. The algorithm creates crash events for one day using the historical crash records (Dataset 1: Crash Records) and matched roadways probability from Tool 1: Crash Road Matching Algorithm. The clearance duration and capacity reduction are also assessed using Dataset 5: Duration and Capacity Reduction of Road Closures. The matching road segment can be either selected from the highest probability roadways or selected randomly using the matching probability. The tool enabled researchers to quickly generate 50 random crash day scenarios in a short time.

Tool 3: Potential Variable Message Sign Location Algorithm

The developed potential VMS location finder tool uses some assured criteria to propose a set of VMS locations based on the current network configuration. These criteria include:

- Located on a freeway road segment.
- Having an immediate exit from the freeway.
- Not overlapped by any existing VMS.

The resulting potential VMS locations help minimize the effort to find the optimal locations in Tool 4: Optimal Variable Message Sign Locator.

Tool 4: Optimal Variable Message Sign Locator

An optimal locator tool was the third goal of the current study after data integration and stochastic emissions reduction calculation for crash events. The mathematical foundation and the optimization pseudocode are outlined as follows.

Mathematical Formulation

The main objective of the location optimization tool is finding the ideal location for conveying information and guidance to users based on the link's potential for time and emissions reductions and at acceptable distances. In other words, an optimized VMS locator should find the links with the highest time and emission reductions for placing VMS while not focusing on a hotspot region. Placing all VMS in the same region causes information redundancy, meaning drivers receive the information they already receive on upstream links, leading to the waste of investment money. Therefore, adding a VMS at each proposed location certifies the reduction in congestion and emissions at downstream links and a minimized impact density for maximizing the spacings between VMS locations and VMS impact areas. A key assumption is that each link can only have up to one VMS. Equation 1 shows the final solution or decision variable for the optimization problem.

$$X = (\, x_1 \,, \; \dots, \; x_i \,, \; \dots, \; x_m) \qquad \text{Equation 1}$$

Where:

$m = number\ of\ links$

$$x_i = \; f(x) = \begin{cases} 1 \text{ , } if\ link\ i\ will\ be\ assigned\ a\ VMS \\ 0 \text{ , } if\ link\ i\ will\ be\ assigned\ no\ VMS \end{cases}$$

Equation 2 and Equation 3 use average traffic delays and emissions results from TEMPO to compute each link's monetary values and costs under crash scenarios compared to no crash scenario. High-cost links show non-recurring congestion and emissions increase, which can be addressed by an upstream VMS. Negative cost links show the roadway was performing better under the crash scenario, probably due to the stochastic network behavior.

$$Link\ j\ value\ function\ (vf^j) = d_c^j * v_{tc} + d_t^j * v_{tt} + e_{ghg}^j * v_{ghg} + e_{Nox}^j * v_{Nox} + e_{PM25}^j * v_{PM25} \qquad \text{Equation 2}$$

$$Link\ j\ cost\ function\ (cf^j) = vf_{incident}^j - vf_{baseline}^j \qquad \text{Equation 3}$$

Where:

$d_c^j = car\ delay\ of\ link\ j, in\ hours$

$d_t^j = truck\ delay\ of\ link\ j, in\ hours$

$e_{ghg}^j = greenhouse\ gas\ (GHG)\ emission\ of\ link\ j, in\ grams$

$e_{Nox}^j = nitrogen\ oxide\ (NO_x)\ emission\ of\ link\ j, in\ grams$

$e_{PM25}^j = particulate\ matter\ 2.5\ microns\ in\ diameter\ or\ smaller\ (PM_{2.5})\ emission\ of\ link\ j, in\ grams$

$v_{tc} = monetary\ value\ of\ time\ for\ cars, in\ dollars\ per\ hour$

$v_{tt} = monetary\ value\ of\ time\ for\ trucks, in\ dollars\ per\ hour$

$v_{ghg} = monetary\ value\ of\ GHG\ emission, in\ dollars\ per\ gram$

$v_{Nox} = monetary\ value\ of\ NO_x\ emission, in\ dollars\ per\ gram$

$v_{PM25} = monetary\ value\ of\ PM_{2.5}\ emission, in\ dollars\ per\ gram$

The rerouting impact of information, provided by a VMS, will gradually decrease by distance from the VMS. That is, a lower number of drivers may reroute in response to a VMS or follow a VMS guidance at further downstream links than upstream links. The researchers refer to the rate of decreasing impact as the attenuation rate and denote it as ρ. Therefore, the current study proposed that the potential for link i to reduce the regional delay and emissions cost is associated with the sum of link j cost reductions multiplied by link j distance from link i for all downstream links within a predefined maximum distance (Equation 4). The link potential is referred to as link utility, and the warning system utility is the sum of all link utilities where a VMS is placed. Adding new VMSs to the system can improve the warning system utility. The current study investigated maximizing the utility improvement function in the optimal locator tool (Equation 5).

$$Link\ i\ utility\ function\ (uf^i) = c_{imp} * \sum_{j=downstream\ links} \left(\rho^{d_i^j} * cf^j\right) \qquad for\ all\ d_i^j < d_{max}$$

Equation 4

$$Warning\ system\ utility\ improvement\ function\ (U) = \textstyle\sum_{i=1}^{m} uf^i * x_i$$

Equation 5

Where:

$c_{imp} = VMS\ impact\ ratio\ on\ cost\ reduction$

$d_i^j = minimum\ distance\ of\ link\ i\ from\ link\ j, in\ miles$

$\rho = attenuation\ rate\ parameter, constant\ between\ 0\ and\ 1$

$d_{max} = maximum\ distance\ a\ VMS\ can\ impact, between\ 2\ and\ 3\ miles$

The other objective function computed in the current study was for impact density criteria (Equation 6). The impact density of a link is a measure representing the cumulative impact of VMS boards on that link. If a link has a high impact density and receives information from a VMS source, it will not be on a priority list for installing a new

VMS. The impact density criteria helped the optimal locator tool to widen the search for VMS locations and not focus on a cost hotspot region. In other words, proposed sites should minimize the local (or link) VMS density (or maximize the distance from other existing VMS locations). Equation 7 shows the warning system density for installing a VMS on link i.

$$Link\ i\ impact\ density\ function\ (sf^{i}) = \sum_{\substack{j=all\ upstream \\ and\ downstream\ links \\ with\ a\ VMS\ sign}} \rho^{d_i^j}\ for\ all\ d_i^j < d_{max}$$ Equation 6

$$Warning\ system\ density\ function\ for\ Link\ i\ (S^{i}) = sf^{i} * x_i$$ Equation 7

Therefore, the objective functions of the current study are shown in Equation 8.

$$Objective\ Functions = \begin{cases} Maximize\ U \\ Minimize\ S^{i}\ for\ all\ i = 1, \ldots, m \end{cases}$$ Equation 8

The constraint of the optimization is the number of proposed VMSs in the network. The current study used all potential VMS locations derived from the previous tool to generate N, the number of the proposed locations for installing VMS boards (Equation 9).

$$Sum\ X = Fixed = N$$ Equation 9

Solution Method

The current study used the Ɛ-constraint method for solving the multi-objective optimization problem in Equation 8 (Haimes, 1971). In the Ɛ-constraint method, the multi-objective optimization is converted into a single-objective optimization by optimizing one objective function and constraining other objective functions to a user-specified Ɛ value. Therefore, the warning system utility from Equation 8 was set as the objective function, and the densities were bounded to a value in Equation 10.

$$Maximize\ U(X),$$

$$Subject\ to: sf^{i} < \mathcal{E}\ for\ i = 1, \ldots, m$$

$$Sum\ X = N$$ Equation 10

The Ɛ-constraint method has multiple advantages over the other multi-objective optimization solution algorithm, the weighting method, including application to non-convex problems and no need to scale the objective functions (Chankong and Haimes, 2008; Mavrotas, 2009). However, specifying the Ɛ value can be challenging. Therefore, the current study took an alternate approach by iterating through different Ɛ values until the solution converges.

Algorithm Pseudocode

The detailed algorithm is described as follows:

1. Generate 50 sets of crash days using Tool 2: Stochastic Crash Generation Algorithm.
2. Compute the link-by-link delay and emissions increase for each iteration using Equation 3.
3. Average the delay and emissions increase for each link over 50 iterations.
4. Set $N, v_{tc}, v_{tt}, v_{ghg}, v_{Nox}, v_{PM25}, c_{imp}, \rho, d_{max}$.
5. Calculate cf^{j} for all link j in the network using Equation 3.
6. Set M as potential VMS links derived from Tool 3: Potential Variable Message Sign Location Algorithm, and set m as the number of potential VMS links.
7. For every i in 1 to m: calculate uf^{i} using Equation 4.
8. Sort M in descending order based on their utility uf^{i}.
9. Set a list for Ɛ with wide ranging values.

10. For every Ɛ in the Ɛ list:
    a. Set i = 1.
    b. For link i in M from step 8:
        i. If uf^i < 0 (meaning the crash scenario did not increase the value functions for downstream links):
            - $x_{i,\ldots,m} = 0.$
            - Go to step 10c.
        ii. Compute sf^i using Equation 6.
        iii. If sf^i < Ɛ:
            - $x_i = 1.$
            - $N = N - 1.$

            Else if sf^i >= Ɛ:
            - $x_i = 0.$
        iv. If N > 0:
            - i= i + 1.
            - Go to step 10b.

            Else if N = 0:
            - $x_{i,\ldots,m} = 0.$
            - Go to step 10c.
    c. Set $X = (x_1, \ldots, x_i, \ldots, x_m).$
    d. Compute delay and emissions reductions, and utility improvement for each selected VMS link and the whole system using Equation 4 and Equation 5.
    e. Go to step 10a if any Ɛ remain in the Ɛ list.
    f. Stop when the set of chosen links stays the same for a sufficiently large number (e.g., 5) of Ɛ values.

End: Set the stabilized X set as the optimal set.

Case Study

The research team selected the El Paso region as a case study. El Paso is located in the southwestern part of the Texas border region with several entry ports to Ciudad Juárez, Mexico. The high cross-border traffic activities and truck traffic have led to poor air quality in the region. El Paso is currently identified as a nonattainment area for particulate matter 10 micrometers in diameter or smaller at an annual averaging period according to the National Ambient Air Quality Standards. Therefore, there is a vital need to reduce traffic-related emissions and improve air quality.

Crash Impacts Analysis

The crash warning database described in the study methodology was developed for the El Paso region to integrate historical crash records, roadway network, travel demand, existing VMS locations, and crash clearance duration. Using Tool 1: Crash Road Matching Algorithm, the current study identified the matching roadway for each crash. Therefore, crash risk (the number of crashes per mile of road per day) averaged over five years of historical crash data was computed. Figure 4 shows some high crash risks on the freeway system.

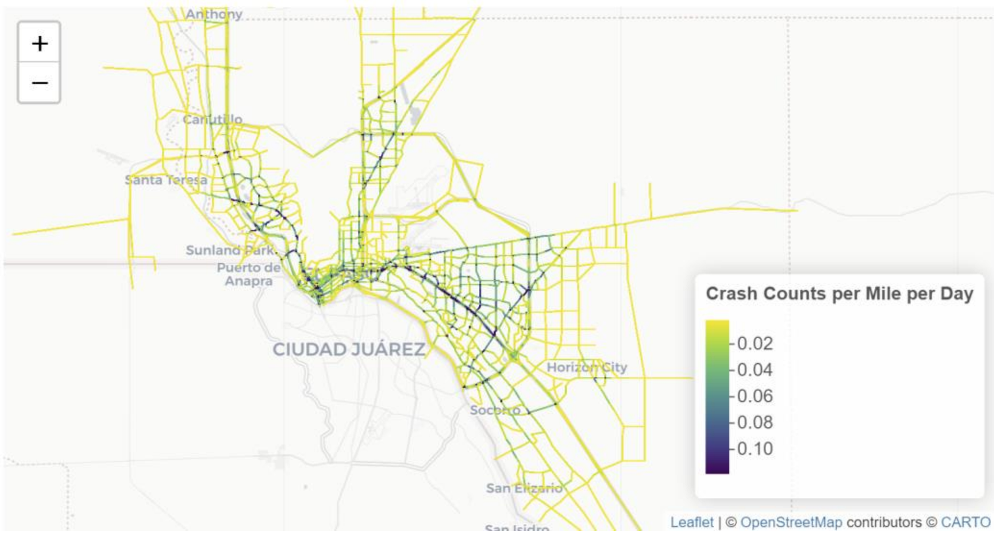

Figure 4. Crash risk of El Paso roadways averaged over five years.

Next, researchers used Tool 2: Stochastic Crash Generation Algorithm and TEMPO to rapidly generate 50 random crash day scenarios. The delay and emissions impacts of crash scenarios are detailed in Table 3. A crash day increases total network delay by 5.6 percent, GHG emissions by 0.7 percent, NO_x emissions by 0.6 percent, and $PM_{2.5}$ emissions by 0.8 percent. The lower relative increase in emissions compared to the relative increase in network delay can be explained by the fact that the emissions rate during idle and at low speeds is lower than that at normal operating speeds. These increases are significant at the 95 percent confidence level, according to the Student t-test. The increase in delay and emissions due to crashes shows the potential for the VMS system to reduce crash-related delay and emissions.

Table 3. Summary Crash Delay and Emissions Impacts

Metric	Increase Value	Percent Increase	P-Value
GHG (ton)	67	0.7%	2.61E-06
NO_x (kilogram)	94	0.6%	2.11E-06
$PM_{2.5}$ (kilogram)	5	0.8%	4.53E-07
Delay (hour)	11,260	5.6%	1.37E-06

Figure 5 illustrates the average delay and emissions impacts of crashes at the roadway level. The maps show that, even though there are minor differences in small sections of the region (e.g., the northwest side), the delays and different emissions species are substantially similar, indicating strong correlations among these metrics. The pattern similarity is further studied in terms of monetary values in the “Aggregate Warning System Utility” section. The road level delay and emissions impacts were integrated into Tool 4: Optimal Variable Message Sign Locator along with the 149 potential locations identified from Tool 3: Potential Variable Message Sign Location Algorithm. Researchers could use further filters to reduce the number of potential VMS locations. However, Tool 4: Optimal Variable Message Sign Locator was designed in a way to handle as many locations as possible. The next section details the optimization scenario design and results for the case study.

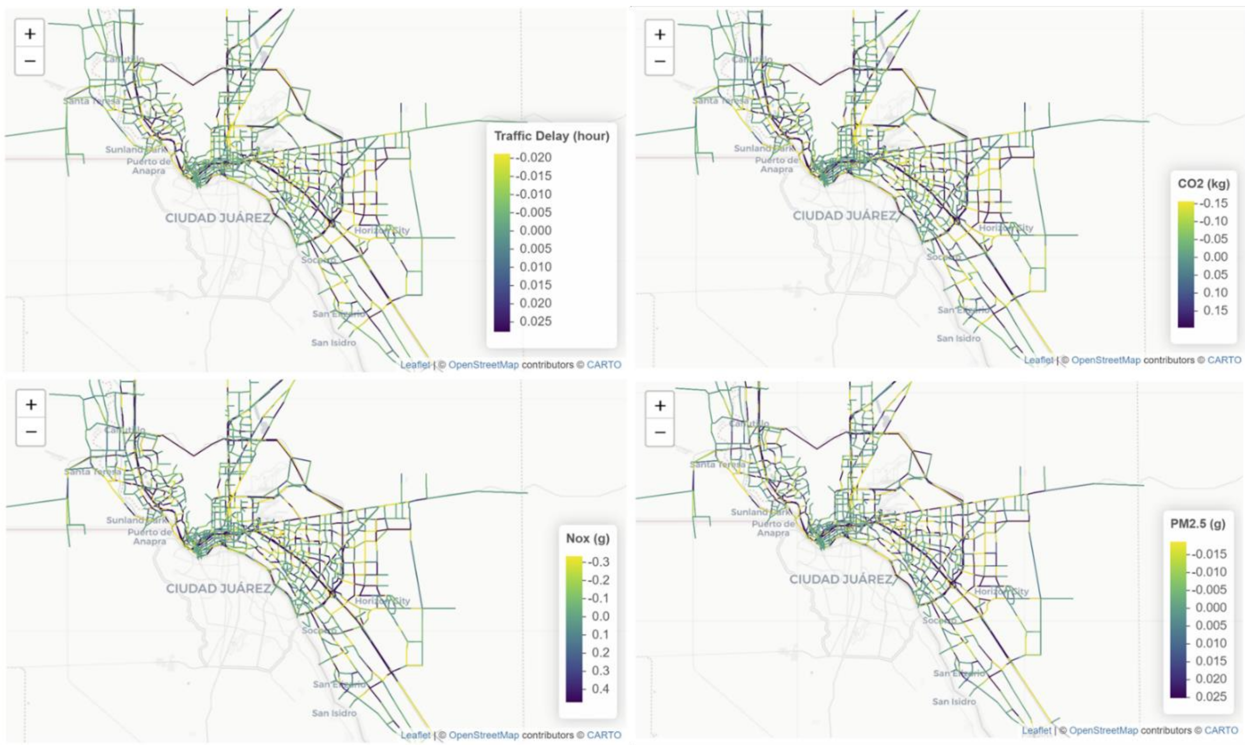

Figure 5. Average delay and emissions impacts of crashes.

Location Optimization of Variable Message Signs

Scenario Design

Intuitively, optimal VMS locations would differ depending on the values assigned to various key input variables outlined in Tool 4: Optimal Variable Message Sign Locator, specifically set in step 4 of the algorithm pseudocode. These input variables can be grouped into two categories:

- the coefficients for the objective function, referred to as hyperparameters, and
- the monetary values assigned to delays and emissions.

The input variables affect the final values for total utility and the relative weight placed on time savings versus emissions reductions.

To search for the optimal solution and test the sensitivity of the solution to these input variables, researchers designed 27 scenarios iterating over a combination of values for hyperparameters of objective function and monetary values. Researchers evaluated the ranking of each potential VMS location under each scenario.

Researchers found that the location sets are not significantly different among most scenarios. The following sections describe the assignment of hyperparameters of objective function and monetary values.

Hyperparameters

The hyperparameters in this study include the VMS impact ratio on cost reduction (c_{imp}), the maximum distance under the impact of the VMS (d_{max}), and the attenuation rate parameter (ρ). Collectively, they define the effectiveness level of a VMS.

The VMS impact ratio on cost reduction (c_{imp}) is assumed to be the same as the VMS impact ratio on congestion reduction from literature. Previous studies have approximated the parameter to be 0.27–0.44 (Barfield et al., 1989; Benson, 1996; Chatterjee et al., 2002; Madanat et al., 1995). Also, the maximum distance under the impact of the VMS (d_{max}) was studied as the activation segment in previous studies and was estimated to be 2–2.5 miles (Chiu and Huynh, 2007; Fan et al., 2018; Wardman et al., 1997). Researchers designed three different effectiveness levels (low, medium, and high) using these two rates (Table 4). The attenuation rate parameter (ρ) is deducted from the activation segment length, considering $\rho^{d_i^j} \approx 0$ for $d_i^j > d_{max}$.

Table 4. Effectiveness Level Scenarios

Effectiveness Level	c_{imp}	d_{max} (mile)	ρ
Low	0.25	1	0.05
Medium	0.35	2	0.22
High	0.45	3	0.37

Monetary Values

The monetary values of time and emissions in Equation 2 are divided into three categories (low, average, and high values) and approximated from the previous studies (Goodkind et al., 2019; Shelton et al., 2014). Table 5 and Table 6 list the values of each category.

Table 5. Monetary Value of Time Scenarios

Monetary Value of Time	v_{tc} (Dollar per Hour)	v_{tt} (Dollar per Hour)
Low	5	10
Average	15	30
High	25	50

Table 6. Monetary Value of Emissions Scenarios

Monetary Value of Emissions	v_{ghg} (Dollar per Gram)	v_{Nox} (Dollar per Gram)	v_{PM25} (Dollar per Gram)
Low	10	1,000	4,000
Average	100	10,000	100,000
High	500	50,000	2,500,000

Scenarios

Finally, researchers designed 27 scenarios using the combinations of the following assumptions for the effectiveness level and monetary values, as well as the number of VMSs for installation:

- Effectiveness level: low, medium, and high.
- Monetary value of time: low, average, and high.
- Monetary value of emission: low, average, and high.

For illustrative purposes, the number of VMSs for installation is set to 10 in this study. Later sections show that this number does not affect the optimal locations of VMSs. An agency can select as many or as few VMS locations as its budget and scope allow.

Optimization Convergence

Researchers iterated over various maximum density, Ɛ in Equation 10, and assessed the average delay and GHG emissions reduction of selected VMS locations in the scenario design (Figure 6). When the maximum density gets high enough (Ɛ > 3 for the low and medium effectiveness levels and Ɛ > 4 for the high effectiveness level), the average delay and GHG emissions reductions converge to the maximum value. Figure 6 shows a convergence point or the minimum value for maximum density. Also, a comparison of the charts on the right side of Figure 6 to those on the left side shows the monetary values of time and emissions may not change the convergence point, or the average delay and emissions reduction at each value of maximum density. The VMS information can impact the traffic activity over a wider area for the high effectiveness level, and the maximum density needs to be higher for substantial delay and emissions reduction. Therefore, the average delay and emissions reduction are lower in the high effectiveness level for low maximum densities. However, increasing the maximum density leverages some locations with wide impact in the high effectiveness level to overcome the previous lack of benefits.

Therefore, the following sections consider maximum density to be equal to 3 for the low and medium effectiveness levels and 4 for the high effectiveness level.

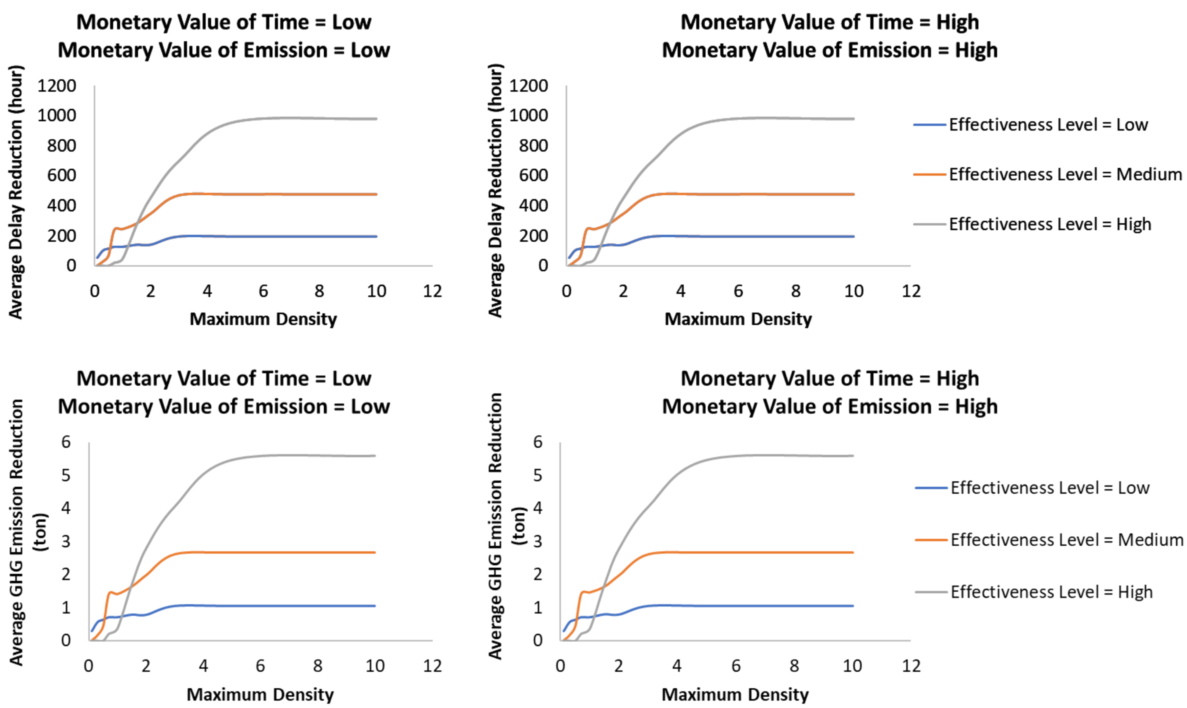

Figure 6. Average delay and GHG emissions reduction of selected VMS locations for various maximum densities.

Aggregate Warning System Utility

Researchers investigated the impact of changes in monetary values of time and emissions on the warning system utility under different effectiveness levels. Figure 7 illustrates the average warning system utility for different monetary values of time and emission, and effectiveness levels. The figure shows that the utility is positively correlated with values of time, values of emission, and effectiveness levels. These assumptions will affect the accounting of the societal return on investment if such analyses are to be carried out for VMS investments.

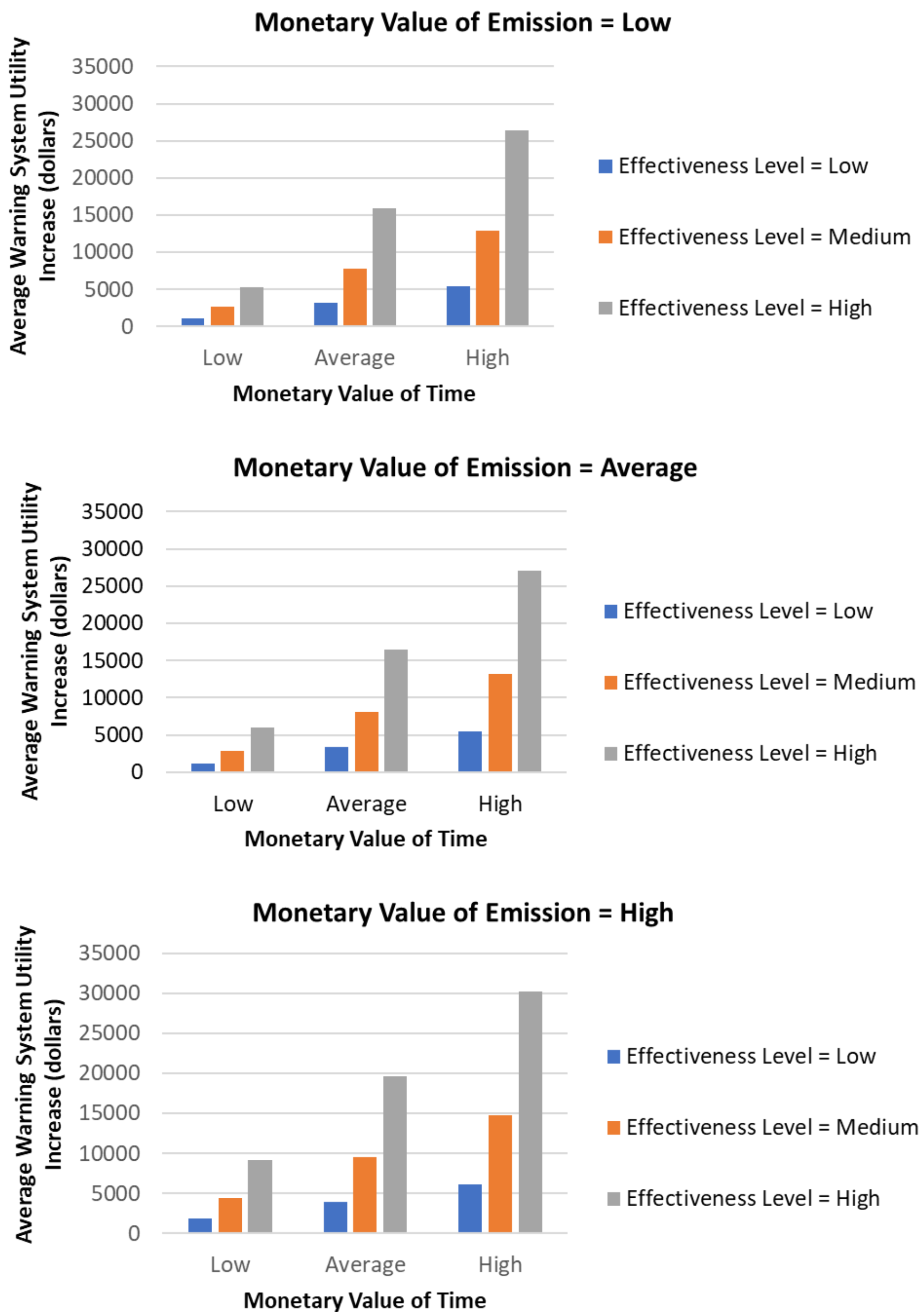

Figure 7. Impact of monetary values of time and emissions on warning system utility.

However, the resulting congestion reduction and emissions reduction from installation of VMSs at proposed locations do not substantially change with the monetary values of time and emissions (Figure 8). That is, the monetary values only impact the warning system utility for the economic decision-making process (Figure 7). However, the selection of optimal VMS locations is not impacted by the monetary values of time and emission, which helps decision makers rely on the proposed locations as long as they have a rough estimate of the monetary values of time and emission.

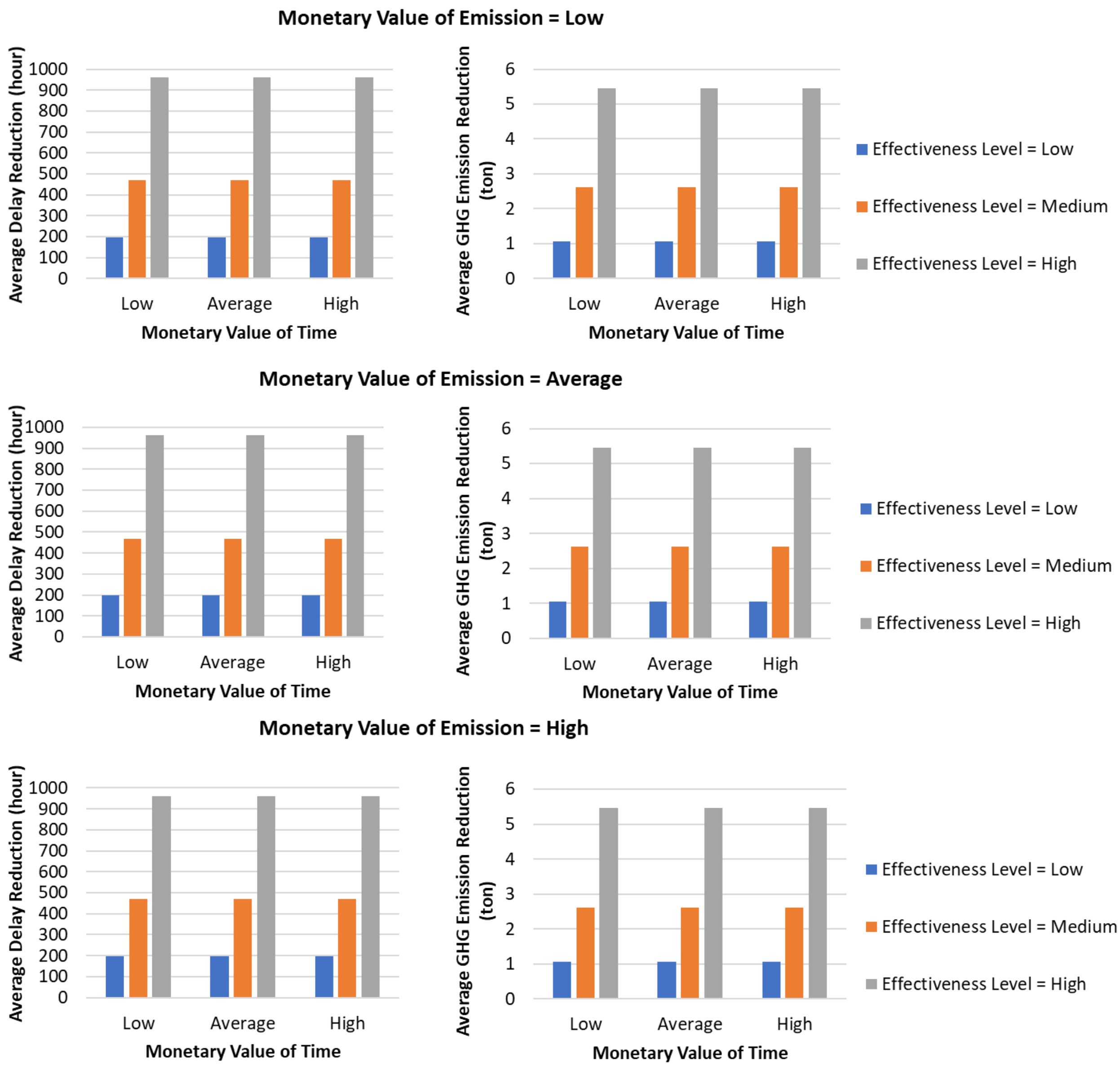

Figure 8. Impact of monetary values on delay reduction and emissions reduction under different effectiveness levels.

The underlying reasons for the insensitivity of average delay benefit and emissions reduction to different monetary levels are:

- Emissions reductions of the downstream links are highly correlated with the delay reduction of those links.
- The delay reduction is a major part of the utility function and higher in value than emissions reduction.

Therefore, emissions benefits can be projected in the congestion reduction, and the utility function can be rewritten in the delay reduction. Figure 9 shows the correlation between emissions reduction and delay reduction of downstream links of all selected VMS links in different scenarios. The correlation between delay reduction and emissions reduction was also previously shown in Figure 5.

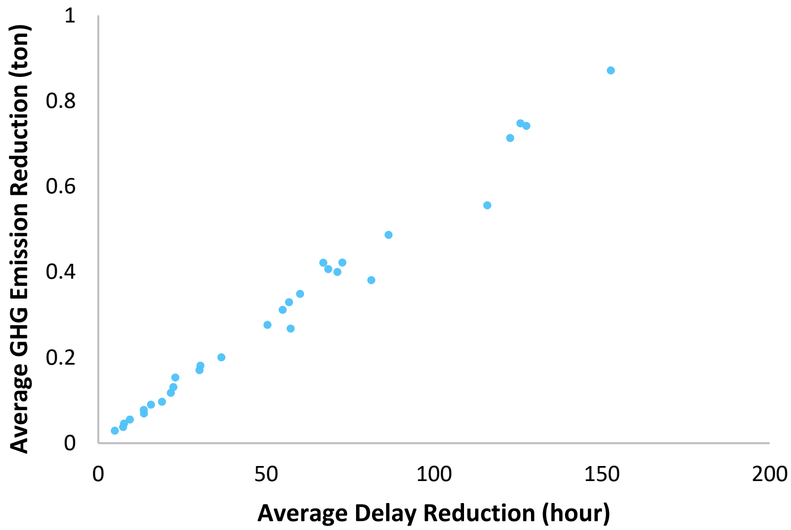

Figure 9. Correlation of delay reduction and emissions reduction of downstream links for 10 selected VMSs across 27 scenarios.

Table 7 shows the average proportion of monetary emissions reduction to delay reduction in warning system utility over different scenarios. As observed, the emissions to delay ratio is mostly insignificant in warning system utility. When selecting high monetary values of emissions and low monetary values of time, the emissions benefits proportion may become more than half of the total utility.

Table 7. Emissions Utility to Delay Utility Ratio

Monetary Value of Emissions	Monetary Value of Time	Effectiveness Level		
		Low	Medium	High
Low	Low	0.011	0.012	0.012
	Average	0.004	0.004	0.004
	High	0.002	0.002	0.002
Average	Low	0.117	0.122	0.124
	Average	0.039	0.041	0.041
	High	0.023	0.024	0.025
High	Low	0.683	0.715	0.730
	Average	0.228	0.238	0.243
	High	0.137	0.143	0.146

So far, the monetary values do not significantly change the delay and emissions reductions of the selected VMS locations. Table 8 shows that even for different effectiveness levels, the first five optimal locations remain the same, and other locations slightly change. Figure 10 maps 10 optimal VMS locations among 149 proposed locations in the El Paso network for the medium effectiveness level.

Table 8. Selected VMS Link Ranks for Different Effectiveness Levels

Link Name	Effectiveness Level = Low	Effectiveness Level = Medium	Effectiveness Level = High
2136-6146	1	2	5
4023-4026	2	1	1
1993-4028	3	3	3
1648-1590	4	4	2
4031-1975	5	5	4
2140-6149	6	10	NA
1659-1658	7	6	7
2871-2870	8	NA	NA
6142-2140	9	9	10
1511-2438	10	8	9
1660-1649	NA	NA	6
1930-1929	NA	7	8

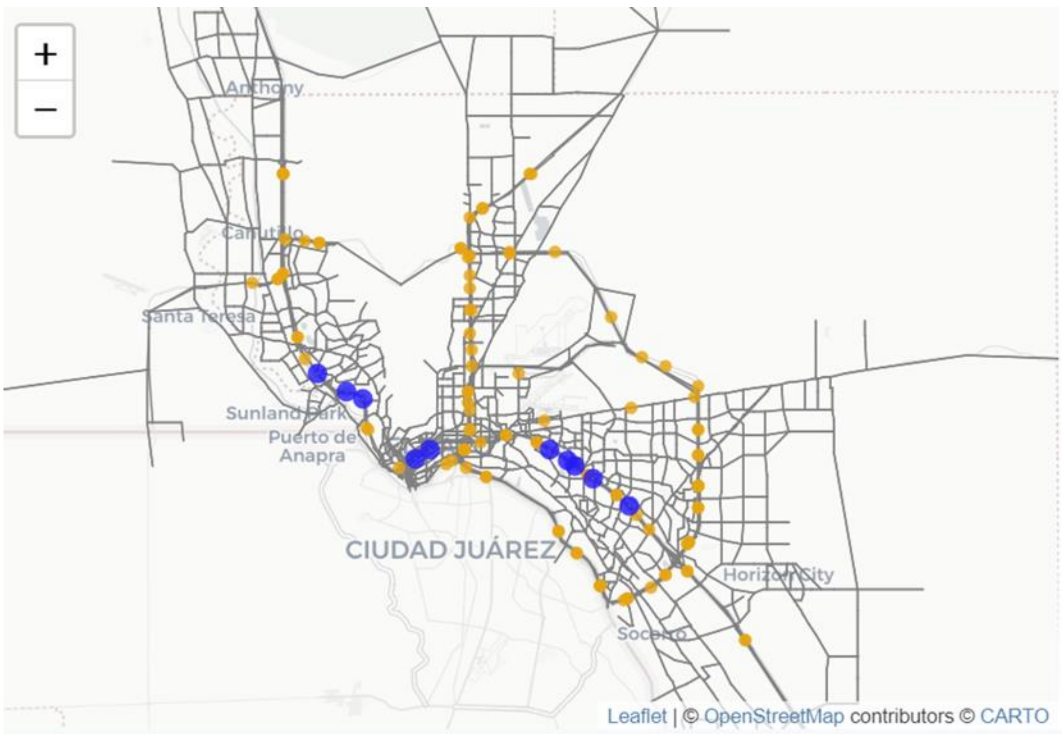

Figure 10. Ten best VMS locations in El Paso for medium effectiveness level (blue points show new proposed locations; orange dots show existing VMS locations).

Marginal Utility of Added Variable Message Signs

Finally, adding each VMS has a different utility benefit to the whole warning system. Researchers monetized this value and estimated them using Equation 4 for all potential VMS links. Figure 11 illustrates the marginal utility of adding VMSs for different effectiveness levels, showing the marginal utility greatly drops after adding the first 10 optimal VMSs to the network and becomes almost significantly small after adding 20 VMSs at optimal locations.

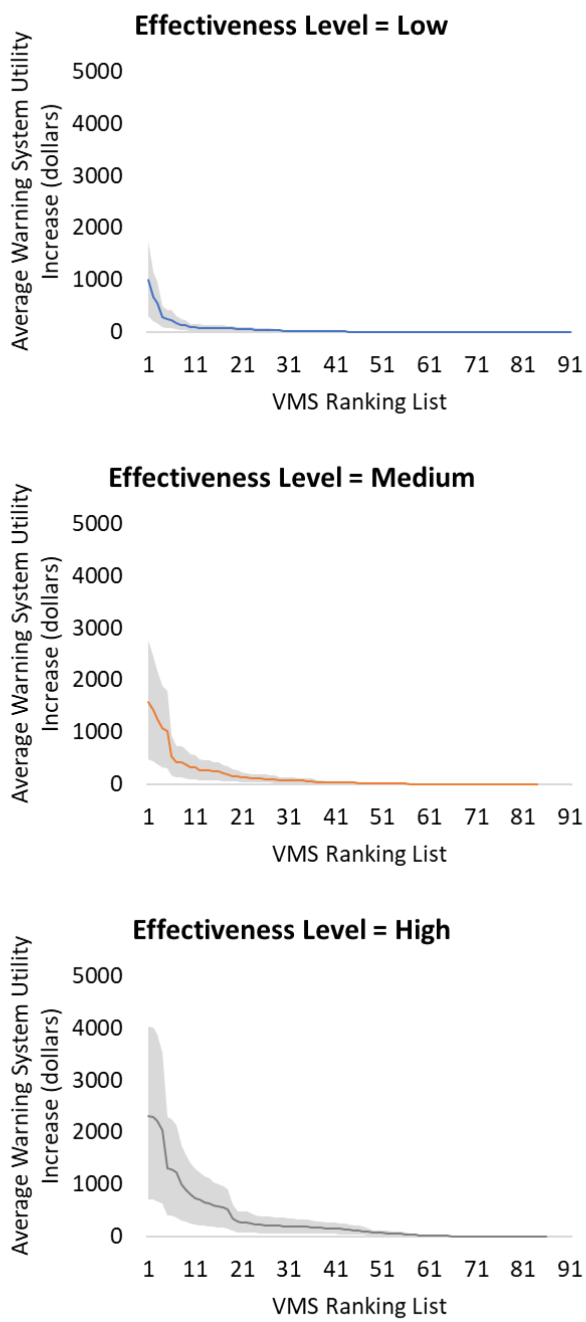

Figure 11. Average delay and GHG emissions reductions of selected VMS locations for different effectiveness levels.

Conclusions and Recommendations

The current study proposed a congestion- and emission-based algorithm to select the optimal VMS locations within a network. The study developed an integrated database and tool framework, TEMPO-Safety, to use historical crash events for assessing the delay and emissions impacts of crashes. Next, the monetary values of these impacts and the optimal VMS locations were identified.

Relationship between Congestion Relief and Emissions Reduction

By studying delay and emissions simultaneously, the study revealed the relationship between congestion relief and emissions reduction. The congestion cost of crashes (excluding the statistical value of life and the medical expenses of injuries) is dominated by the lost value of time. Emissions cost constitutes up to 15 percent of total congestion cost, under low and average pollutant costs. Emissions changes are highly correlated with delay changes in the network. The relative increase in delay caused by crashes is much higher than the relative increase in emissions. Traffic management mechanisms such as VMSs are mostly a congestion relief measure, but their emissions reduction efficacy is limited.

Societal Benefits of Optimally Placed Variable Message Signs

The study results have demonstrated the value of ITS strategies such as VMSs. Ten optimally placed VMSs can save $1,000–9,000 per day depending on the value of time, value of emission, and effectiveness level. VMSs can reduce the delay by 200–900 hours per day, which is less than 8 percent of the crash delay increase. The GHG emissions may be reduced by 1–5 tons per day, which is 1–8 percent of the total GHG emissions increase caused by crashes. The marginal benefit of adding more VMSs decreases dramatically after 10 or so additional signs for the El Paso network.

According to data from the U.S. Department of Transportation, a low estimate of the capital cost per VMS unit is $100,000 (U.S. Department of Transportation, 2012). Ten VMSs, as suggested in this study, would amount to $1 million in capital cost. Referring to the benefits range, a $5,000 per day savings would add up to $1.3 million in societal cost savings, considering 260 weekdays in a year. This rough estimate demonstrates the favorable return on investment for VMSs if they are optimally placed.

Future Work

This project devised an optimization method to place VMSs. This methodology can be generalized to other infrastructure improvement problems where decision-makers need to find an additional amount of an infrastructure element and place these elements among many potential locations. The project team plans to further validate and refine the methodology by applying it to a different network and experimenting with a similar but different decision-making process.

Outputs, Outcomes, and Impacts

The main output of this project is the TEMPO-Safety framework, with its four tools for automating crash matching, crash generation, location identification, and location optimization in a network system. The tools made it possible to sample multiple crash days for statistical rigor and iterate over multiple input assumptions to search for the optimal solution set.

With the automated process, the study demonstrated a practical solution for minimizing delay and emissions impacts in networks. This solution can lead to major financial and societal cost reduction through infrastructure decision-making. Furthermore, the optimization algorithm can be extended to other infrastructure decision-making processes involving location selection.

Research Outputs, Outcomes, and Impacts

The proposed platform and case study findings were accepted for a webinar talk at the National Travel Monitoring Exposition and Conference 2021.Researchers are also preparing a publication draft and anticipate that the location optimization part will be the basis for a doctoral dissertation.

Technology Transfer Outputs, Outcomes, and Impacts

A dashboard has been produced to generate spatial locations for various crash metrics as well as the final VMS location design: https://carteehdata.org/library/webapp/crash-warning-emission-da-14b7.

A data story and visualizations have been shared on the CARTEEH Data Hub for public access: https://carteehdata.org/library/dataset/crash-warning-emission-da-c3cf. The transferability of the proposed methodology can also be ensured through open-source codes and libraries.

Education and Workforce Development Outputs, Outcomes, and Impacts

The key analyst for this project is Farinoush Sharifi. She was a third-year Ph.D. student in transportation engineering at Texas A&M University at the time of the project and looking forward to using the findings of this research as support for her final dissertation. This project was also a unique opportunity for her to gain insight into a cross-disciplinary research area, as well as to work through a project from proposal to finish, which is not offered as part of the traditional curriculum. Along with completing the tasks in the research plan, she benefited from reviewing previous work, learning the procedure to obtain datasets, collaborating with experts, and managing a project.

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