The Effects of Detector Spacing on Travel Time Prediction on Freeways

Piyali Chaudhuri, Peter T. Martin, Aleksandar Z. Stevanovic and Chongkai Zhu

Abstract—Loop detectors report traffic characteristics in real time. They are at the core of traffic control process. Intuitively, one would expect that as density of detection increases, so would the quality of estimates derived from detector data. However, as detector deployment increases, the associated operating and maintenance cost increases. Thus, traffic agencies often need to decide where to add new detectors and which detectors should continue receiving maintenance, given their resource constraints. This paper evaluates the effect of detector spacing on freeway travel time estimation. A freeway section (Interstate-15) in Salt Lake City metropolitan region is examined. The research reveals that travel time accuracy does not necessarily deteriorate with increased detector spacing. Rather, the actual location of detectors has far greater influence on the quality of travel time estimates. The study presents an innovative computational approach that delivers optimal detector locations through a process that relies on Genetic Algorithm formulation.

Keywords—Detector, Freeway, Genetic algorithm, Travel time estimate.

I. INTRODUCTION

INDUCTIVE loop detectors are installed on many freeways in the United States. Loop detectors monitor traffic conditions at single-point locations. They supply data about traffic conditions: vehicle presence, flow, occupancy and speed. Flow and occupancy may be extracted directly from loop data; however, algorithms must be developed to calculate point speed and travel time. Evaluation of freeway performance is based on the information derived from loop detectors. The reliability and accuracy of these data depends on the number and placement of loop detectors. Proper placement enables transportation agencies to derive more accurate information for performance monitoring, which in turn improves traffic operation activities overall, such as ramp metering. However, as Departments of Transportation (DOTs) deploy more detectors, the associated operating and maintenance cost increases [1]. So, traffic agencies need to decide where to add new detectors and which detectors should be maintained, given their resource constraints [2].

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A Traffic Monitoring Station (TMS) is defined as a set of inductive loop detectors that covers each mainline and ramp. TMS reports traffic characteristics in real time and are at the core of the traffic management process. Utah Department of Transportation (UDOT) has deployed TMSs on I-15 in Salt Lake City metropolitan region at approximately ½ mile spacing. This half mile spacing is a product of early requirements for real-time data collection and is used to manage traffic and provide driver information. With the advent of advanced video surveillance such as Closed Circuit Television (CCTV) technology, the use of these data for incident detection has become less important. However, there are other important uses of the data that have different requirements for TMS placement. For example, we need to estimate travel time from TMS detector data. This is feasible if the TMSs are placed so that they can sample freeway conditions effectively. There is a tradeoff between the intensity of TMS spacing and the accuracy of travel time estimates. Intuitively, one would expect that as the density of detection increases, the quality of travel time estimates also increases. However, this improved accuracy comes with a cost: installation and maintenance.

The literature shows that the effect of field detection spacing on traffic forecasting measures along freeways has been addressed. For a 9 mile Californian route, Kwon et al. [3] showed how derived congestion measures such as total delay, extent and duration of congestion, vary with the number of detectors. They infer that the accuracy of estimates increases in proportion to the number of detectors deployed. However, the authors did not focus on travel time estimation. Ozbay et al. [4] investigated the effect of sensor location on travel time estimation during recurrent and non-recurrent congestion on I-76 in southern New Jersey. They found that increasing the number of sensors does not always improve the accuracy of travel time estimates. Bartin et al. [5] showed that the marginal gain of travel time accuracy decreases as the number of road-based surveillance units increases. By selecting the detectors in a pre-defined way, Fujito et al. [6] studied the effect of detector spacing on travel time index (congestion measure), using field data from Cincinnati, Ohio, and Atlanta, Georgia. Their analysis did not show any definite pattern of the variation of travel time index with detector spacing. Chan et al. [7] proposed a bi-level programming model to determine the speed detector density with travel time information. They showed that Root Mean Square Error (RMSE) of average link travel time estimate decreases with increase in the number of speed detectors. In a similar study, Sen et al. [8] showed that the measured travel time errors are nonlinear and inversely proportional to the number of probe vehicles. Ban et al. [9] indicated that as sensor spacing increases, travel time estimation becomes more sensitive to actual sensor

locations. Chen *et al.* [10] studied how short-term traffic forecasting performance is related to detector spacing using neural networks. They concluded that forecasting performance was not significantly affected by detector spacing. Cheu and Ritchie [11] reviewed several incident detection algorithms applied to sites with both dense and sparse arrays of detectors. They reported no clear link between performance and detector spacing.

To summarize, the literature shows research that addresses the relationship between field detection and the estimation of traffic metrics is active, through methods that can be characterized as modeling [4],[5],[9] or empirical [3],[6]-[8]. Chen *et al.* [10] has tested their modeling findings with empirical data from field. However, their work addressed short-term forecasting, not travel time estimating. There is need for further work. Methods validated by field data needs to be developed. Further, there is a need for methods that address detector error. In concluding, the literature for travel time estimates is inconsistent and hence inconclusive.

The goal of this paper is to determine the impact of decreasing TMS coverage on a freeway corridor on the computation of congestion measures such as travel time estimates. In other words, how is the inaccuracy of the travel time estimates affected by increased TMS spacing? The paper analyzes the sensitivity between the accuracy of travel time estimates and TMS spacing. Several hypothetical uniform spacing cases are examined: 0.5, 1, 1.5, 2, 2.5, 3 miles. Field data comes from the Interstate-15 (I-15) freeway in Salt Lake City metropolitan area. Travel time estimates from speeds collected from field detectors are compared to travel time estimates derived from micro simulation. This would ensure the robustness and applicability of the methodology. A further analysis adopts a metaheuristic method to develop Pareto optimal solutions to the multi-criteria optimization problem. Resulting Pareto optimal solutions would deliver a robust and compromise design of the optimal location of TMS.

Solving single objective optimization problems by Genetic Algorithms (GAs) has become a proven and widely accepted technique. Genetic Algorithms are heuristic optimizers based on the evolutionary concepts of natural selection and survival of the fittest [12]. Genetic Algorithms has also been found to be most successful in multi-objective optimization [13]. In this paper, a Pareto based multi-objective GA is applied to the simultaneous optimization of travel time accuracy and number of TMSs.

II. METHODOLOGY

A novel computational approach was developed to meet the study objectives. The study segment is the I-15 freeway between 800 south in Salt Lake City (SLC) to 400 south in Orem, Utah. The 35 mile study corridor has the TMS spacing of approximately ½ mile. The baseline scenario represents the average TMS spacing. With the baseline scenario of half-mile spacing and increasing the spacing in increments of half-mile up to three miles produces six uniform TMS spacing scenarios (0.5, 1, 1.5, 2, 2.5 and 3 mile). Deleting alternating TMSs from the baseline (0.5 mile) scenario creates the 1 Mile scenario. This generates two scenarios: the odd numbered TMSs (1010101), and the even numbered TMSs (0101010). The same procedure was repeated for the other uniform TMS spacing between 1.5 Mile and Mile 3, to generate 21 TMS spacing scenarios.

Table I lists the TMS spacing scenarios generated for analysis.

TABLE I
TMS SPACING SCENARIOS

Name	Average distance between TMS (mile)	Scenarios: No of possible data sets	No of TMS skipped
Baseline	0.5	1	0
Mile 1.0	1.0	2	1
Mile 1.5	1.5	3	2
Mile 2.0	2.0	4	3
Mile 2.5	2.5	5	4
Mile 3.0	3.0	6	5
Total		21	

The freeway study section is divided into 57 Zone of Influence (ZOI) sub segments which are defined as half the distance upstream and downstream to the neighboring TMS as shown below in Fig. 1.
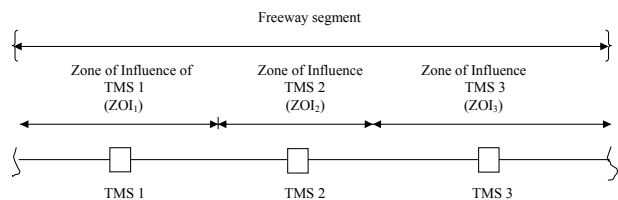

Fig. 1 Freeway section and zones of influence for TMS

The spot speeds from detectors that constitute a TMS were used to calculate the travel time over the entire ZOI. Travel time for each TMS is given by the ZOI length divided by the spot speed across the TMS. The travel time for each of the constituent ZOIs was calculated and summed to give the total estimated travel time for the entire freeway segment. The difference between the estimated travel time and the actual travel time is the travel time error for the freeway segment.

Travel time estimates from field analysis were compared to travel time estimates derived from simulation in VISSIM [14] for validation purpose. The field analysis is pertinent to the cases when existing TMS layouts should be revisited in order to find if removing redundant stations would reduce costs of their operations and maintenance without affecting quality of the travel time estimates. However, the field analysis cannot be used to plan for new facilities and to develop a new TMS layout on the freeways which are currently not detectorized. For such purposes one can use microsimulation models, which accurately resemble field traffic operations. Fig. 2 illustrates the methodology used to compare field analysis with high-integrity simulation analysis.

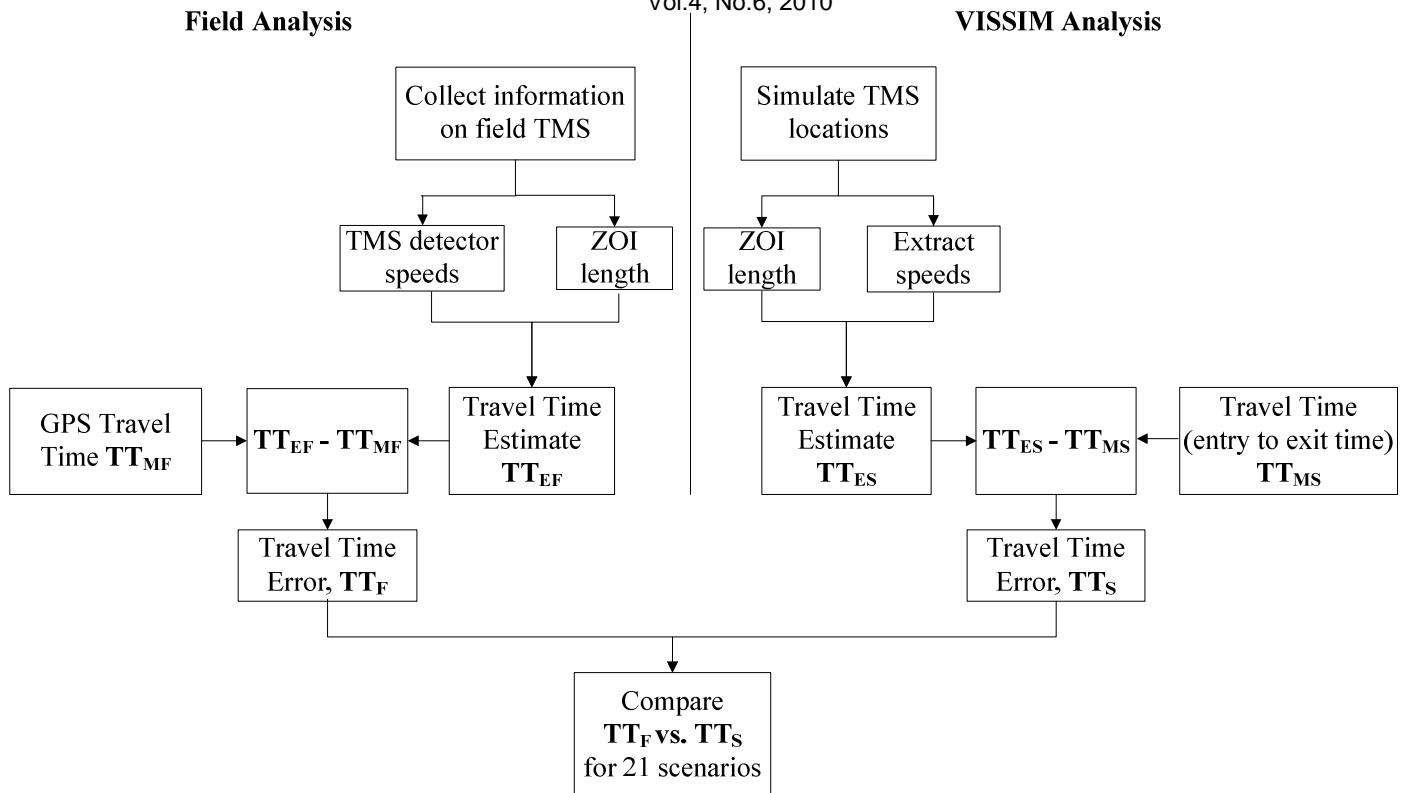There follows a detailed explanation of the field analysis and the Simulation (VISSIM) analysis.

Field Analysis   **VISSIM Analysis**

Fig. 2 Steps involved in Field and VISSIM Analysis

A. Field Data

Field data was collected from the TMSs on the I-15 freeway (800 south in SLC to 400 south in Orem) in the Salt Lake City metropolitan area. The loops are mostly dual loop detectors which give direct measure of speed data. In some cases, there are radar units (Wavetronix model 105) that deliver the same data as single loop detectors. They apply a speed algorithm that presents an average speed based on the occupancy numbers for the prior 16 vehicles.

UDOT reports the 20-second loop detector speeds for purpose of real time traffic management applications. The 20-second data are imported in real-time to VISUM-Online, a program now called PTV Traffic Platform, to facilitate further archival and analysis [15]. The measures were recorded at 20-second intervals. The detector speeds were then extracted.

The field data was extracted for the morning peak period traffic on Tuesdays, Wednesdays, and Thursdays for the month of August, 2007. Flawed or aberrant data due to road work or detector failures were excluded from the analysis. The mean of spot speeds from detectors that constitute a TMS were used to calculate the travel time over the entire ZOI. Travel time for each TMS is given by the ZOI length divided by the aggregated spot speed. The estimated travel time (TT_{EF}) is the sum of travel times of the constituent ZOIs of the freeway segment. For measured travel time (TT_{MF}) computation, Global Positioning System (GPS) travel time for the entire freeway section was utilized. The GPS speed data was collected using the Floating Car Technique. In this technique, a GPS device was installed in the vehicle that was driven according to the "flow of traffic" throughout the study segment [16]. While the vehicle is running, the GPS device automatically logs the latitude and longitude and the time data [17]. Altogether 96 GPS runs were completed. The difference between the TT_{EF} and TT_{MF} gives the travel time error (TT_F) for the entire freeway segment. In a similar manner, the travel time errors for all 21 TMS spacing scenarios were estimated.

B. Simulation

The VISSIM model of the freeway study segment was developed for a recent High Occupancy Vehicle (HOV)/High Occupancy Toll (HOT) study [18]. Building, calibrating and validating the VISSIM model required extensive field data collection and data reduction. Various traffic data were collected between 6.30 AM and 9.00 AM (morning peak) on Tuesdays, Wednesdays, and Thursdays, under fair weather and dry pavement conditions during four weeks in August, 2007. Other periods were excluded because the traffic was light. Both the network and the model input were based on actual peak period traffic data of the I-15 corridor. Detail description of the data, calibration, and validation results is documented [17], [18]. Validation results showed a very close match between travel times from field and simulation. Further, UDOT provided the locations of the installed TMS along I-15 on a KMZ file in Google Earth software [19], providing a realistic background image. The image enables users to easily navigate through a network. Using this tool, the specific location of the TMS were identified and added into the existing I-15 model as data collection points. Fig.3 represents the VISSIM model of I-15 for an intersection showing the built in data collection points which resembles the actual TMS locations obtained from the Google Earth KMZ file.

VISSIM generated the spot speeds at the built-in TMS locations. These spot speeds served to calculate the travel time over the entire ZOI. Travel time for each TMS is given

by the ZOI length divided by the spot speed. The estimated travel time (TT_{ES}) is the sum of travel times of the constituent ZOIs. Two travel time sections, one at the entry and one at the exit of the freeway segment were built into the model to obtain the measured travel time (TT_{MS}) for the freeway segment. The difference between the TT_{ES} and TT_{MS} is the travel time error (TT_S) for the entire freeway segment. The procedure was repeated to calculate the travel time errors for all 21 TMS spacing scenarios.

TT_i - Travel time for ZOI$_i$ ($TT_i = \dfrac{ZOI_i}{V_i}$)

TT_E ($=TT_{EF}$ or TT_{ES}) - Estimated travel time for the freeway

section ($\sum_{i=1}^{n} TT_i$)

TT_M ($=TT_{MF}$ or TT_{MS}) - Measured travel time for the freeway section

ε - Estimation Error $= \left| TT_E - TT_M \right|$

Travel time for each ZOI is estimated from the speed data obtained at the TMS location. The length of the ZOI divided by this speed gives the travel time value ($TT_i = \dfrac{ZOI_i}{V_i}$) at each TMS location. TT_E for the entire freeway section is obtained by summing individual travel time estimates (TT_i) for all constituent ZOIs ($\sum_{i=1}^{n} TT_i$). The travel time error is given by:

$$\varepsilon = \left| \sum_{i=1}^{n} TT_i - TT_M \right| = \left| \sum_{i=1}^{n} \frac{ZOI_i}{V_i} - TT_M \right| \qquad (1)$$

For the first TMS in the freeway section,

$$ZOI_1 = x_1 + (\frac{x_2 - x_1}{2}) = (\frac{x_1 + x_2}{2}), \text{ for i = 1} \qquad (2)$$

For all intermediate TMSs in the freeway section,

$$ZOI_i = \frac{x_{i+1} - x_{i-1}}{2} \qquad (3)$$

For the last TMS in the freeway section,

$$ZOI_n = (L - x_n) + (\frac{x_n - x_{n-1}}{2}) = L - (\frac{x_n + x_{n-1}}{2}),$$

for i = n $\qquad (4)$

Substituting (2), (3) and (4) in (1), the travel time error becomes:

$$\varepsilon = \left| \{(\frac{x_1 + x_2}{2V_1}) + \sum_{i=2}^{n-1} (\frac{x_{i+1} - x_{i-1}}{2V_i}) + L - (\frac{x_n + x_{n-1}}{2V_n})\} - TT_M \right|$$
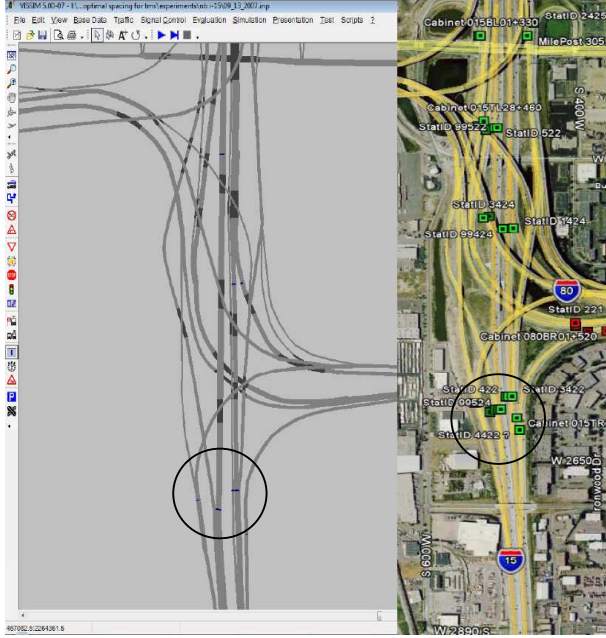
$\qquad (5)$

Fig. 3 Model of a part of I-15 showing built-in TMS locations resembling those in KMZ file

III. FORMULATION OF THE TRAVEL TIME ERROR FUNCTION

Travel time error is the difference between the measured travel time and the estimated travel time required to travel a roadway segment. This concept was used in the formulation of the travel time error function. The analytical approach followed is similar to the approach reported by Edara *et al.* [20]. Two specific travel time estimates are defined: Measured Travel Time (TT_M) and Estimated Travel Time (TT_E). TT_M represents the actual travel time required to traverse the freeway section. The notation and formulations are discussed as follows:

Notation:

n - Number of TMSs on the freeway section (= number of zones of influence)
i - Index of the ith TMS
L - Length of the freeway section
x_i - The distance from the origin of the freeway section to the ith TMS location
ZOI_i - Length of Zone of influence of the ith TMS

$$L = \sum_{i=1}^{n} ZOI_i$$

V_i - Speed reported by the ith TMS

IV. RESULTS

A. Travel Time Prediction with Field Data

Fig. 4(a) and 4(b) summarizes the results obtained from field data analysis. Fig. 4(a) shows that there is a weak trend between travel time error for different TMS spacing. However, the spread appears to be big and varied with the increase in TMS spacing. There are inconsistencies which do not follow the trend such as: specific scenarios in Mile 1, Mile 2.5 and Mile 3. This is probably due to the actual location of TMS in those scenarios. Similar observations are noted in Fig. 4(b), which provides the relationship between travel time error versus the number of TMS deployed for 21 detector spacing scenarios. There appears to be a weak relationship between travel time error and number of TMS deployed with some anomalies. These anomalies are likely

due to the difference in the location of TMSs in different scenarios.

Fig. 4 Field Results (a) Travel time error as a function of TMS spacing (b) Travel time error as a function of number of TMS deployed

B. Travel Time Prediction with Simulation Data

Fig. 5(a) and 5(b) present the results obtained from the micro simulation using VISSIM. Fig. 5(a) shows the plot of the travel time errors versus TMS spacing for different spacing scenarios. Similar to the field results, there is a weak relationship between the travel time error and TMS spacing. However, the spread appears to become broad and varied with the increase of TMS spacing. Further, there are some scenarios that deviate from the general trend. This is likely due to the location of TMS in an individual scenario. Fig. 5(b) provides the relationship between the travel time errors and the number of TMS deployed for 21 spacing scenarios. There appears to be weak trend suggesting some correlation between the travel time error and the number of TMS deployed with few anomalies.

Fig. 5 Simulation Results (a) Travel time error as a function of TMS spacing (b) Travel time error as a function of number of TMS deployed

C. Comparison between Simulation and Field Results

Fig. 6 presents the comparison between travel time errors obtained from field versus simulation using VISSIM. The travel time error for all 21 scenarios were plotted to facilitate the comparison. The plot shows that the micro simulation is closely consistent with the field based analysis ($R^2 = 0.85$). Comparing both Figs. 4 and 5, it is observed that VISSIM model underestimates travel time error by about 2 min; however this underestimation is consistent and therefore does not significantly affect the overall relationship between travel time error and number of TMSs. Further, the good correlation between the travel time error derived from cleaned field measurements, and micro simulation, suggests that the findings are reliable. Comparison between both data also proves the validity of the methodology. Table II provides a summary of the travel time error obtained from simulation and field data analysis. It is evident that there is a broad and varied trend that suggests that as the TMS spacing increases, so does the

error. However, there are many inconsistencies to the general trend. This is likely due to the actual location of the TMSs in the scenarios. Simply put, optimal detector placement is essentially idiosyncratic. So, bland generalized modeling of freeway segments will deliver sub-optimal locations which would be little better than location guesses made by a traffic engineer. There is a need to determine the optimal number and location of TMS which requires a sound and robust optimization technique.
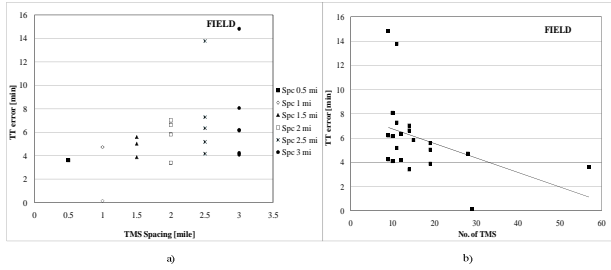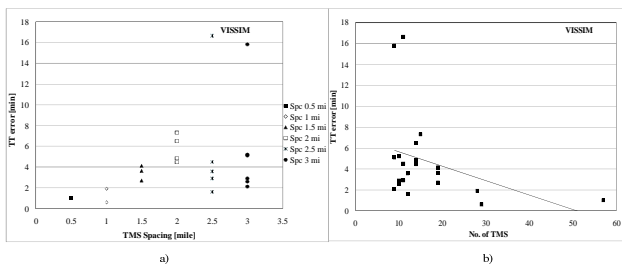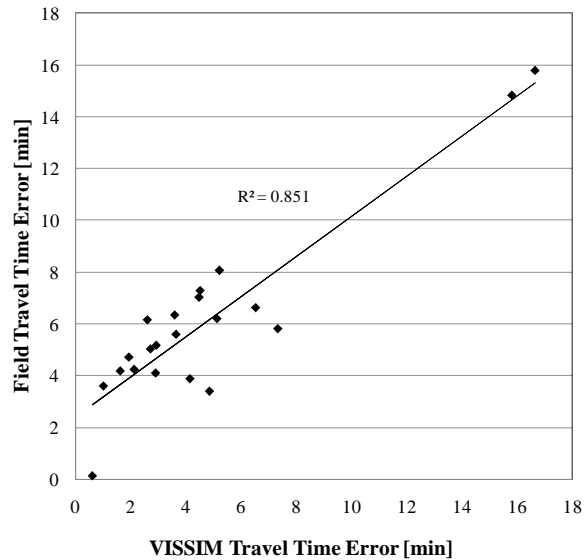

Fig. 6 Comparison between Simulation and Field results

TABLE II
SUMMARY OF TRAVEL TIME ERROR FOR TMS SPACING

Scenarios	TMS Spacing (mile)	No. of TMS	Travel Time Error (min)		Average Travel Time Error (min)	
			Field	Simulation	Field	Simulation
Baseline	0.5	57	3.61	1.01	3.61	1.01
1	1.0	29	0.14	0.61	2.43	1.27
2	1.0	28	4.72	1.93		
1	1.5	19	5.04	2.71	4.84	3.50
2	1.5	19	5.60	3.64		
3	1.5	19	3.89	4.14		
1	2.0	15	5.82	7.32	5.72	5.79
2	2.0	14	3.41	4.85		
3	2.0	14	7.03	4.47		
4	2.0	14	6.63	6.52		
1	2.5	12	6.35	3.59	7.76	5.86
2	2.5	12	4.19	1.62		
3	2.5	11	15.78	16.64		
4	2.5	11	5.18	2.92		
5	2.5	11	7.29	4.51		
1	3.0	10	8.07	5.21	7.27	5.63
2	3.0	10	4.11	2.90		
3	3.0	10	6.16	2.60		
4	3.0	9	6.21	5.12		
5	3.0	9	14.83	15.80		
6	3.0	9	4.25	2.12		

V. OPTIMAL LOCATION OF TMS

The problem of the placement of TMS within a roadway network is not unique. It belongs to the broad field of location theory that deals with the placement of infrastructure facilities in a given space by optimizing certain desired objectives [21]. Literature shows that operations research techniques, especially optimization, have been used successfully to determine the optimal location of desired facilities, such as placement of detectors for O-D estimation, AVI readers for travel time estimation etc [5], [22], [23].

However, unlike some other location theory problems, problem of placing TMSs within roadway, in such a way to minimize both number of TMSs and travel time estimation error, cannot be easily reduced to a single-objective optimization problem. Sometimes, multi-objective optimization problems are transformed into single-objective optimization problem by finding a 'common denominator' by which both of the objectives can be represented. The 'common denominator' is often expressed as a monetary value. In this problem, however, costs can be assigned to number of TMSs (e.g. operating and maintenance costs) but it is very difficult to assign a monetary value to the fact that there is an error in estimated travel time. Our ability to accurately estimate travel time does not directly impact the traffic conditions in the field.

In such a situation, when multiple objectives are present, a front of Pareto optimal solutions can be very helpful. By using Pareto front decision-makers can visually recognize solutions that will fit their current goals regarding one of the objectives and yet making sure that they get the best of the other objective, in the solution they selected. Pareto optimal set are feasible solutions that are not dominated by any other solutions. A Pareto-optimal solution cannot be improved upon without hurting at least one of the criteria.

During the past two decades, GAs has successfully been used for optimization of difficult problems. Unlike most conventional search algorithms, GA's search from a population of points, producing an entire set of solutions as the optimization outcome. Foundations of GA are found in Goldberg [12] and a comprehensive survey with engineering applications is given by Gen and Cheng [24]. The interest in application of GAs in the area of detector location is still in its early stage. One study has illustrated GA application to evaluate optimal placement of detectors on Virginia's freeways [20]. However, the results were based on single objective optimization of the travel time estimate function. The optimal location problem is essentially an iterative process involving conflicting objectives and constraints. A better approach is to look upon this design problem as a multiobjective optimization problem. Genetic algorithms have also been found to be most successful in multi-objective optimization [13]. In this paper, the Nondominated Sorting Genetic Algorithm II (NSGA II) proposed by Deb et al. [25] is applied to simultaneously optimize (minimization) the competing objectives: travel time error and number of TMS. This will deliver optimal number and location of TMSs. NSGA-II is a heuristic multi-objective optimizer based on the genetic algorithm optimization approach. It is one of the most popular and best performing multi-objective genetic algorithms [26]. To achieve a robust algorithm, a Pareto optimal scheme is applied to ensure a near optimal Pareto solution [27].

The proposed algorithm (NSGA-II) generates a Pareto optimal subset from which a robust and compromise design can be selected. Through iteration of the optimizer, the population will converge toward a Pareto front, which describes a near-optimal trade-off curve. Existing literature shows that the Pareto-based multi objective GA has not been used in the optimization of detector locations.

A. Using NSGA-II to Optimize TMS locations

An intuitive way of representing a solution for the TMS location problem is using a string of cells as shown in Fig. 7.
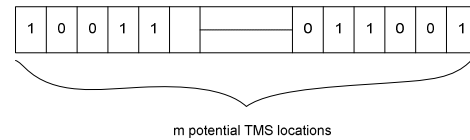

Fig. 7 Solution representation

The study area is divided into m discrete cells and each cell corresponds to a potential TMS location. The value in the cell indicates the existence of a TMS. A value of 1 means that a TMS is deployed at that location and a value of 0 means there is no deployment. The sum of all cell values, or the length of the string, is equal to the number of TMS to be deployed.

The NSGA-II is evaluated using the aforementioned binary encoding of the decision variables. The aim of the algorithm is to simultaneously optimize both travel time error, ε (Refer to 5) and the number of TMS, n, to arrive at a solution that delivers the optimal number and locations of TMS. A population of size 100, a uniform crossover (probability of 0.98), and a mutation probability of 0.01 are used in the algorithm. The NSGA-II is run for 250 generations. Field data for I-15 NB for August'07 (AM peak period) was used in the algorithm. Fig. 8(a) shows the step-by-step procedure how the NSGA-II algorithm works.

Initially, a population of individuals, P_o (size N=100) is created in the search domain. Then, the fitness (objective) functions for the individuals are calculated. The usual tournament selection, recombination, and mutation operators are used to create an offspring population Q_o of size N. A combined population $R_n = P_n \cup Q_n$ is formed. The population is of size 2N. Next step is to sort the population based on non domination. Each solution is assigned a fitness (or rank) equal to its nondomination level (1 is the best level, 2 is the next-best level, and so on). The next step involves discrimation between individuals with identical domination rank. This is performed by favoring individuals in less crowded regions of the objective space. This encourages the discovery of a diverse approximation to the Pareto set. Fig. 8(b) shows schematically how the sorting based on nondomination and crowded distance works in the nth generation. Since all previous and current population members are included in R_n, elitism is ensured. Now, solutions belonging to the best nondominated set F_1 are of best solutions in the combined population and must be emphasized more than any other solution in the combined population. If the size of F_1 is smaller than N, we definitely choose all members of the set F_1 for the new population P_{n+1}. The remaining members of the population P_{n+1} are chosen from subsequent nondominated fronts in the order of their ranking. Thus, solutions from the set F_2 are chosen next, followed by solutions from the set F_3, and so on. This procedure is continued until no more sets can be accommodated. Say that the set F_n is the last nondominated set beyond which no other set can be accommodated. In general, the count of solutions in all sets from F_1 to F_n would be larger than the population size. To choose exactly N population members, we sort the solutions of the last front F_n using the crowded-comparison operator in descending order and choose the best solutions needed to fill all population slots. The new population P_{n+1} of size N is now used for selection, crossover, and mutation to create a new population Q_{n+1} of size N.
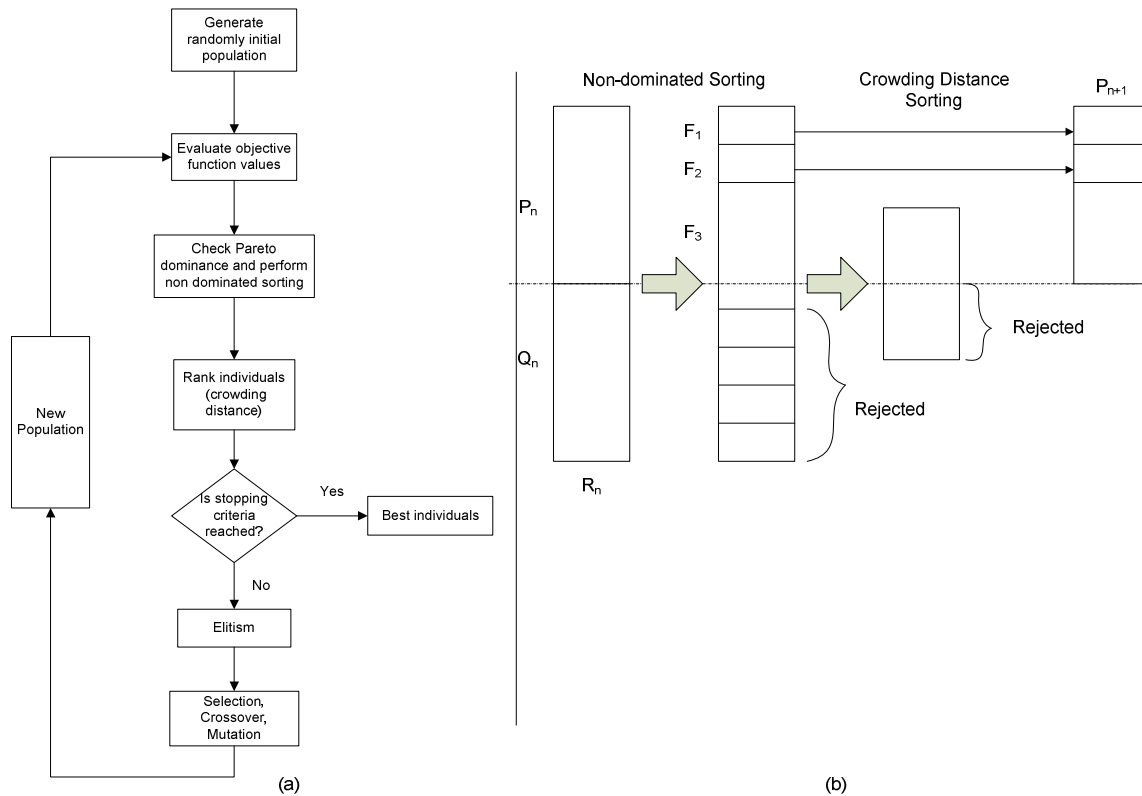
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Fig. 8 NSGA-II algorithm (a) Flowchart of algorithm (b) Procedure at n[th] generation

The diversity among nondominated solutions is introduced by using the crowding comparison procedure, which is used in the tournament selection and during the population reduction phase. Solutions that dominate other solution are favored for selection by a tournament selection procedure. Tournament selection randomly choose a few (the exact number is based on evolution pressure) individuals and then always take the single best individual. In the next step, crossover and mutation are employed to generate new children from the selection procedure. Crossover allows for the combination of useful traits. Mutation induces random alterations to the decision variables to allow for the examination of new search points as well as the restoration of lost genetic material. An elitist replacement scheme is used to determine the constituents of the subsequent generation by combining the parent and the child populations and keeping only the N best individuals based on domination ranks.

B. Results from NSGA-II

Results of the NSGA-II runs for the I-15 NB section are shown in Fig. 9, 10, 11and 12. The results for the best variant of NSGA-II (uniform crossover, tournament selection) were investigated. Several optimization runs corresponding to different random seeds were examined to arrive at the best pareto optimal solution. The Pareto front generated by multi-objective optimizer for TMS location problem is graphed in Fig. 9.
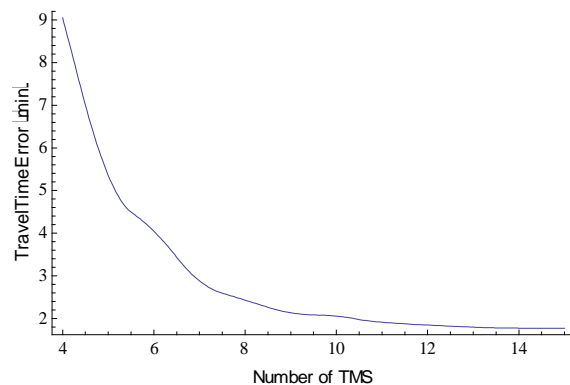
Fig. 9 Pareto front for NSGA-II

The Pareto front consists of the set of objective vectors associated with the Pareto optimal set. Pareto optimal set are those solutions that are not dominated by any other solutions. These solutions represent the best possible compromises with respect to the competing objectives of optimizing both travel time error and number of TMS. The plot shows that the error value is high when only a few TMSs are deployed; however, as the deployment increases the error value decreases. After reaching approximately 10 (strategically-located) TMSs, any further increase in the number of TMSs may not significantly decrease the error. The optimal placement of 13 TMS gives an accurate estimate of travel time. The corresponding location of these 13 TMS as obtained from the optimization program is

shown in Fig. 10. Fig. 11 depicts a three-dimensional plot showing the convergence of the algorithm over 250 generations. As the number of generation increases, the algorithm reaches convergence and generates the Pareto front of the optimal solutions. In the first 100 generations, most of the individuals use a larger number of TMS and travel time error is high. As the number of generation increases, the Pareto front is starting to get a shape-the algorithm finds that a lower number of TMSs can achieve the same (or smaller) low travel time error. In addition, the algorithm tests some solutions with only few detectors and it finds that these solutions generate very high travel time errors. After 200 generations, the results seem to have reached an optimum level between both the competing criteria. Fig. 12 shows the number of times a potential TMS location is present in the optimal solution. This plot specifies the location of the most critical TMS along the study stretch. The TMSs which lie on the zero line are not important. TMSs which are between 0 and 6 (excluding 6) are moderately important, whereas the TMSs which are placed 6 or more times in the optimal TMS solution are very important. Of the 13 sets of TMS deployments, for example, locations 22, 36, 41 and 42 are selected 11 times. This indicates that these locations are critical for TMS deployment. Location 22 corresponds to the TMS located immediately downstream of the I-215 interchange (Belt Route) and locations 36, 41 and 42 are located near the interchange of UT-154/Bangerter highway (Fig. 10).
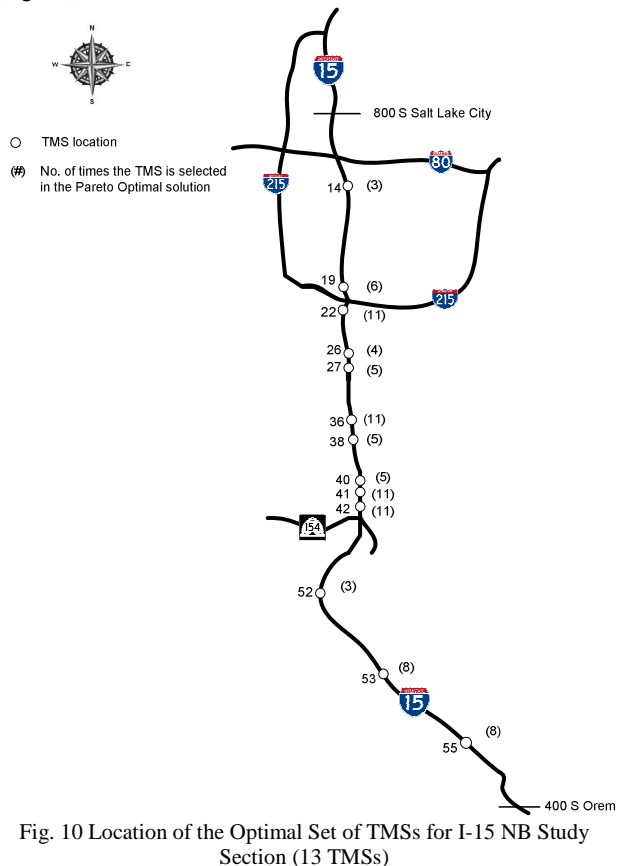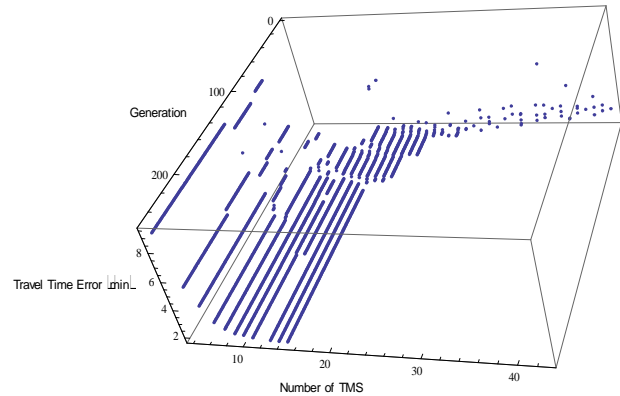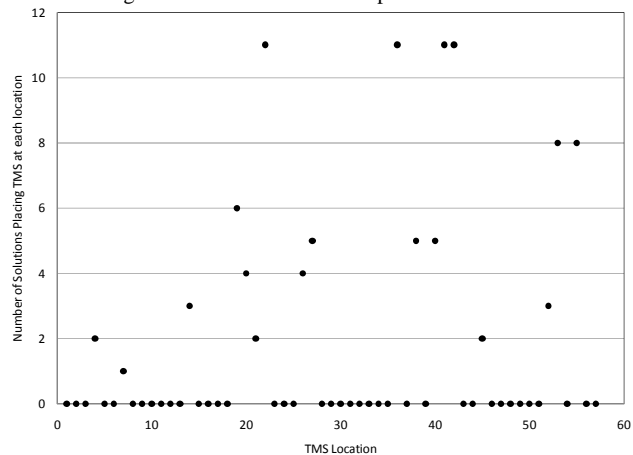

Fig. 11 Attainment of Pareto optimal solution

Fig. 12 Frequency Plot showing the Number of Times a TMS is placed at Each Location (I-15 NB, August'07, AM Peak)

VI. DISCUSSION

Results have shown that traffic performance in terms of travel time estimate was not affected significantly by uniform TMS spacing. With the increase in uniform TMS spacing (0.5 to 3 mile) the travel time error tend to increase, however the relationship is weak. There appears to be a broad and varied spread of travel time error with the increase of TMS spacing. There are some scenarios whose travel time errors tend to deviate from the general trend. Part of the complexity is attributed to the actual location of the TMSs. This is because some scenarios might contain TMS in some locations which would translate into overestimating or underestimating the travel time error. This indicates that there is a certain placement of TMSs that provide better traffic performance in terms of travel time estimates than the other placements. Assuming that the cost of TMS infrastructure is proportional to the number of TMSs installed, higher density does not seem to pay off, as the costs rises sharply for little return in accuracy.

Further analysis using NSGA-II algorithm generated the Pareto front that consists of the optimal solutions. These solutions represent the best possible compromises with respect

Fig. 10 Location of the Optimal Set of TMSs for I-15 NB Study Section (13 TMSs)

to the competing objectives of optimizing both travel time error and number of TMS. Results suggest that optimal placement of 13 TMS would outperform 57 TMS installed at 0.5 mile spacing (approximately). This is because the average of travel time derived from TMSs included in the baseline scenario depresses the actual congestion at the congested areas on the freeway. Results indicate that these locations are critical for travel time computations and the TMSs deployed in these locations need to be regularly maintained. One of the outputs of the algorithm is the frequency plot that gives the number of times a TMS is placed at any location on the corridor for different sets of TMSs. Locations with high frequencies are the ones that are most critical for deployment and/or maintenance. Results showed that TMS at locations 22, 36, 41 and 42 are crucial to obtain accurate travel time estimates on the study corridor. In general, the developed method shows that the TMS density needs to be higher in congested areas of a corridor. Un-congested sections of the corridor need only a nominal deployment. Therefore, the general philosophy of more is better is only applicable for congested sections of freeway corridors. It was found that TMSs (22, 41, 42) are required at merge areas near entrance ramps, especially when the acceleration lanes are short. This can be attributed to the potential reduction in traffic speeds in merge areas due to increased weaving.

VII. CONCLUSION

The goal of this paper is to determine the impact of decreasing TMS coverage on a freeway corridor on metrics such as travel time estimates. The methodology developed in this study to calculate the travel time error was effective in determining the sensitivity analysis between TMS coverage and travel time estimate. Findings suggest that there is a relationship between travel time errors with respect to the TMS spacing. More TMSs are not necessarily better. Rather, the quality of estimates varied with TMS spacing and location. The analysis shows that actual location of the TMS is the key element in the estimation of travel time for the freeway section. Depending on the TMSs "selected", a different picture for the congestion measure along the freeway section can be obtained.

Further analysis shows that selection of specific placement of the TMSs is essential in obtaining valid measures of travel time. Results indicate that substantially fewer TMSs are needed for accurate travel time prediction than was true for incident detection. With carefully placed TMS detectors that are well maintained, travel time estimates can be derived with an acceptable level of accuracy. Overall, it is essential to deploy more TMSs to cover major bottleneck areas and nominal for free-flow regimes. These findings suggest that highway agencies can reduce the number of TMSs currently maintained and can deploy far less than the current half- mile spacing guidelines. This could save in capital expenditure, operations, and maintenance costs. Further, the successful application of NSGA-II algorithm showed the potential of using the optimization formulation in this problem. Results reveal that the presented approach is promising as an engineering design tool.

This empirical study illustrates the effect of TMS spacing on travel time accuracy under non-incident conditions. Incident conditions were not tested within the scope of this study. Including information on incidents, road conditions, road geometry, and work zones in the analysis may help in developing guidelines to support freeway performance measures. To sum up, the reliability of travel time estimates depends on the network specific idiosyncratic location of detector stations; and less on the overall density of detector coverage.

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