EVALUATION OF OPTIMAL TRAFFIC MONITORING STATION SPACING ON FREEWAYS

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LIST OF ACRONYMS

GPS	Global Positioning System
GA	Genetic Algorithm
TMS	Traffic Monitoring Stations
UDOT	Utah Department of Transportation
UTL	Utah Traffic Lab
ZOI	Zone of Influence

EXECUTIVE SUMMARY

Traffic Monitoring Stations on Interstate 15 in Utah's Salt Lake City metropolitan region are placed at approximately 0.5 mile spacing. It is time to replace and upgrade the detectors that constitute these Traffic Monitoring Stations. The 0.5 mile spacing owes little to logical design. Where the new detectors should be deployed and how many of them are required is the focus of this project.

The research reported here has two parts. The first part evaluated the effectiveness and reliability of the detectors in traffic monitoring stations deployed by the Utah Department of Transportation (UDOT) on Interstate 15 (I-15). The purpose of the second part of the project was to develop an analytical methodology to calculate travel time measures considering the trade-off between spacing and accuracy of the estimates. The project identifies the optimal locations of a finite set of point detectors on the freeway corridor in order to minimize the error in travel time estimation, within the constraints of available capital and state maintenance funding.

The freeway section (I-15) between 800 South in Salt Lake City to 400 South in Orem was chosen as the study section. While there are other potentially important uses of the data collected by freeway point detectors, the recommendations in this report deal specifically with travel time estimation. It is often assumed that the scenario with the smallest sensor spacing (i.e., greater density of sensors) is the one closely capturing actual traffic conditions. However, the project answered the question "If detector spacing is increased, how will the quality of the traffic data be affected?" Several uniform spacing cases (0.5, 1, 1.5, 2, 2.5, and 3 mile) were examined to obtain a relationship between spacing and accuracy of travel time estimates. Detector speed data from both VISSIM micro simulation and the field were used in the analysis. The investigators found that there is no systematic variation of the travel time error with respect to the detector spacing. The analysis showed that the actual location of the detector is important in the estimation of travel time for the freeway section. Depending on which detectors are "selected," one can obtain a rather different picture for the congestion along the freeway section. Further analysis by strategically selecting detectors located near congestion/bottlenecks and other important locations along I-15 showed that UDOT can reduce the number of detectors currently maintained by TMCs and can deploy far fewer than the 0.5 mile spacing guidelines.This should result in significant cost savings in capital, operations, and maintenance costs. Further, we propose the future work that will enhance the robustness of the methodology in evaluating the optimal spacing of the traffic monitoring stations on I-15.

1. INTRODUCTION

Inductive loop detectors are installed on many freeways in the United States. Loop detectors monitor traffic conditions at single-point locations wherever the detector is located. They supply several pieces of 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 the loop detectors. The reliability and accuracy of these data depend on the allocation and placement of loop detectors. Through proper placement of loop detectors, transportation agencies can derive more accurate information for performance monitoring, which in turn would improve traffic operation activities overall, such as ramp metering. On the other hand, as DOTs deploy more detectors, 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.

The research reported here has two parts. The first part evaluates the effectiveness and reliability of the detectors in traffic monitoring stations deployed by the Utah Department of Transportation (UDOT) on Interstate 15 (I-15). The second part evaluates the optimal placement of detectors considering the trade-off between spacing and accuracy of the estimates.

UDOT deployed traffic monitoring stations (TMS) on I-15 in the Salt Lake City metropolitan region at approximately 0.5 mile spacing. A TMS consists of a set of inductive loop detectors that covers each mainline and ramps. This spacing is a product of early requirements for real-time data collection and used by traffic management centers in the region to manage traffic and incidents and provide information to the motorists about prevailing conditions. With the advent of closed circuit television (CCTV) technology, the use of these data for incident detection has decreased to some extent. There are other important uses of the data that likely have different requirements for detector placement than the original incident detection focus. For example, there is a desire to derive travel time estimates from the detector data. This is feasible if the detectors are placed so that they can sample the freeway conditions effectively. Unfortunately, there is little guidance on how to place these detectors for effective sampling. Further, as deployment increases, the operating and maintenance cost associated with these detector systems also increases. Therefore, there is a tradeoff between detector spacing and accuracy of travel time estimates. As detectors become more closely spaced, the accuracy of the travel time estimate increases. However, this additional accuracy comes with much higher capital as all detectors require regular maintenance to continue to report accurate data. UDOT is, therefore, seeking a method to indicate the most appropriate locations for detector deployment. The criterion is to minimize the travel time estimate error within the constraints of available capital and maintenance funding.

Limited research to date has been devoted to develop computationally tractable methods for optimal detector placement for travel time estimation on freeways. In general, the methods to solve this problem in the scientific field are: Simulation Method, Algorithmic Method, Geometric Method, and Optimization Method. Most of the studies rely heavily on simulated data from different micro-simulation software, such as CORSIM or PARAMICS. However, they provide no conclusive evidence supporting any one technique over the other. Efforts to compare different speed-based travel time estimation models were found to underestimate the actual travel times. There is no evidence validating any particular estimation algorithm over the other. Studies have focused on the evaluation of the sensor density, however, the question on optimal location of sensors remains unanswered.

The research reported here details an analytical technique to calculate travel time error considering the trade-off between detector spacing and accuracy of travel time estimates. This tool analyzes the sensitivity between “estimated accuracy of travel time” and “number of detectors” (or total maintenance costs). This leads to recommend the optimal placement of detectors for the available funding. In the first part of the project, the accuracy and reliability of the TMS on the freeway section was examined. The methodology involved the comparison of the GPS speed data (*1*) with the TMS detector speed data to assess the reliability of the TMS. The loop detector speed data were derived from the VISUM-Online (V-On) software now called PTV Traffic Platform. These data were then extracted from their original *xml* file format and converted into *txt* format. This was done by means of several algorithms and computer coding.

This process provided the detector speed data for the second part of the project, which consists of evaluating the optimal placement of the detectors. Several hypothetical uniform spacing cases (0.5, 1, 1.5, 2, 2.5, and 3 mile) are examined to obtain the relationship between spacing and accuracy of travel time estimates. Detector speed data from both VISSIM micro simulation and the field are used in the analysis. The results quantify the trade-off between spacing and the accuracy of travel time estimates. Further analysis shows that the actual location of the detector is an important factor in the estimation of travel time for freeways. The picture of the freeway congestion depends on which detectors are selected. Further analysis shows the importance of strategically selecting detectors located near congestion/bottleneck and other important locations along I-15.

A review on the research publications relevant to detector placement is presented in Section 2, with the detailed description of the methodology of detector data collection and procedure in Section 3. The data analysis and results are discussed in Section 4, followed by the conclusion drawn from the study in Section 5. Suggestions for future work are in Section 6.

2. LITERATURE REVIEW

The optimal detector placement problem is a less explored research topic in transportation. Limited research to date has focused on the placement of detectors for freeways with respect to travel time estimation. In general, the methods to solve this problem in the scientific field are: Simulation Method, Algorithmic Method, Geometric Method, and Optimization Method.

For a 9-mile route in California, Kwon et al. (*2*) studied how congestion parameters such as total delay, extent, and duration of congestion vary with the number of detectors. They infer that accuracy of estimates increases with the increase in the number of detectors. By selecting the detectors in a pre-defined way, Fujito et al. (*3*) studied the effect of detector spacing on travel time index, using field data from Cincinnati, Ohio, and Atlanta, Georgia. Their analysis concluded that the actual placement of detectors was critical in accurately estimating the congestion levels on the corridor. Bartin et al. (*4*) proposed a clustering based approach for determining the optimal roadway configuration of detectors for travel time estimation in New Jersey. The developed approach was illustrated using simulation experiments. Liu et al. (*5*) presented a study for examining some widely used travel time estimation methods with different detector spacing. The travel time estimation approach they investigated included a constant speed based (CSB) algorithm, a piecewise constant speed (PCSB) algorithm, and piecewise linear speed based (PLSB) algorithm for section level travel time estimation, and instantaneous and actual travel time for corridor level travel time estimation. They built a simulation model for the I-70 corridor in Maryland and found that for free flow conditions it is sufficient, for both monitoring and travel time estimation, to have detector stations placed at both ends of the segment as long as the detector data are reliable. In addition, the study found that for congested segments, more detectors certainly provide a better estimate of travel time variation. Based on these findings, they proposed rules and an iterative procedure for locating a limited number of detectors. Li et al. (*6*) compared the performance of four different algorithms (or models): an instantaneous model, a time slice model, a dynamic time slice model, and a linear model. All models compute freeway segment travel times by aggregating the travel times of constituent sections (with detectors at the beginning and end of a section). They are, however, different in the way that they estimate the section travel times. The instantaneous model uses speeds reported by detectors at an instant of time *t*. The time-slice and dynamic time-slice models use speed values at the time points when the vehicle is expected to travel on each section. The linear model interpolates speeds within a section instead of averaging the speeds of beginning and ending detectors. Results showed that the estimated travel time error for the four algorithms was similar as they under-predicted the travel times. However, the purpose of this study was not to determine the optimal detector locations, but instead to determine the best method to estimate freeway segment travel times.

Ban et al. (*7*) formulated the dynamic programming algorithm to determine optimal sensor locations. Unlike other studies, they tested the model and algorithm using both simulated data and real data from GPS-equipped cellular phones. Results showed that it is optimal to place more sensors in bottleneck areas and just a few in the free flow areas. A study by Bertini (*8*) described a concept based on the first principles of traffic flow theory. The study evaluated optimal sensor density based on the magnitude of under- and over-prediction of travel time during shock passages when using a midpoint method. Edara et al., (*9*) developed a methodology to identify the optimal locations of detectors on freeway (Northern Virginia, I-66 corridor) by minimizing the travel time estimation error. The Genetic Algorithm tool derived the optimal locations of the detectors by increasing the detector density in congested areas of a corridor and only nominal deployment in uncongested areas. The study also considered the trade-off between the detector spacing and the accuracy of travel time estimates. Further, traffic bottlenecks are one of the leading causes of freeway delay and by far the most important location for the placement of sensors. Upstream of a bottleneck, vehicle densities are higher while speeds are lower. Downstream of the bottleneck, on the other hand, vehicle densities are lower while velocities are higher. This means that additional sensors should be placed around bottleneck areas where traffic conditions are most turbulent. A study by Liu and Danczyk (*10*) developed a model for optimally locating roadway loop detectors for performance measuring purposes. This model maximizes the total benefit by allocating loop detectors relative to a bottleneck's location and is constrained by monetary and spatial limits. Benefit is determined to be the variation of average speed between any two eligible detector-allocating locations over a given time period. Using the cell transmission model on a pipeline freeway, this paper demonstrates the model's successful ability to place detectors near known bottlenecks. On a case study network with bottlenecks in unknown locations, the model successfully allocates loop detectors to locations where bottlenecks are most likely occurring.

This review shows that there are little research efforts in detector placement field with respect to travel time estimation. In most cases, the studies rely heavily on simulated data (*4*, *5*) from different micro-simulation software, such as CORSIM or PARAMICS, thereby providing no conclusive evidence supporting any one technique over the other. Efforts on the evaluation of different speed-based travel time estimation models found to underestimate the actual travel times by 4 to 6 minutes during the peak periods (*6*). Further, no evidence validating any particular estimation algorithm over the other exists (*5, 6*). Using the midpoint method, a study has focused on the evaluation of the sensor density; however, the question on optimal location of sensors remains unanswered (*7*). Studies on Optimization method provided some useful results on the allocation of the loop detectors using field data considering a trade-off between number of detectors and accuracy of travel time estimates. However, the benefit of allocating a certain number of detectors over the other for a marginal increase or decrease of travel time estimate was not addressed (*9*). This benefit factor was addressed in one of the optimization studies, however, the paper did not focus on the optimal detector placement for a freeway section (*10*).

Some studies have estimated travel time from available field data which came from the loop detectors (*9, 10*). The optimal detector placement in this regard has not been widely studied. There is a need for validation of their results with simulation data. This is essential considering the low reliability and accuracy of the field detector data (*11*).

This research addresses the gap between other studies that deals with the optimal placement of detectors on freeway sections. An objective function is formulated that considers the trade-off between detector spacing (and number of detectors) and the minimum travel time error. The study compares results using both the simulated data from VISSIM micro simulation software and the field detector data. Further, we will investigate the problem using a genetic algorithm to converge on a small, user-defined subset of acceptable solutions, in the Pareto-optimal (P-O) range (*13*). Solutions in the P-O set will represent the best possible compromises with respect to the competing objectives. The P-O analysis will enable us to incorporate the benefit term in our analysis and give a better justification on the allocation of the optimal number of detectors with respect to the minimum travel time error.

3. METHODOLOGY

The analysis was done using both VISSIM micro simulation and field speed data from the detectors to achieve the study objectives. A description of each of the methods follows.

3.1 VISSIM Analysis

A model of I-15 between 800 South in Salt Lake City to 400 South in Orem was built in the VISSIM micro-simulation software. UDOT provided the locations of the installed TMS along I-15 on a KMZ file in Google Earth software *(12)*. Google Earth provides a realistic background image. Their image enables users to easily navigate through a network. Using this tool, the actual location of the TMS was identified and added into the I-15 model as data collection points. Figure 1 represents the VISSIM model of I-15 for an intersection showing the built-in data collection points that resembles the actual TMS locations from the KMZ file in Google Earth. Both the network and the model input were based on actual traffic data of the I-15 corridor. Successful evaluation of the model generated the speed data at the desired TMS locations, which were used for further analysis.

After the required speed data were obtained, several uniform spacing cases were tested. For the purpose of this study, the baseline detector spacing condition was represented by an average spacing of 0.5 mile (the detector spacing that is actually present in I-15). Baseline condition was chosen where no detectors were deleted. It was assumed that the utilization of all the detectors would give a more accurate reading of the actual congestion levels. Starting with the baseline scenario of 0.5-spacing, and increasing the spacing in an increment of 0.5-mile, led to 3-mile spacing, which produced six different uniform spacing cases (0.5, 1, 1.5, 2, 2.5, and 3 mile). In order to generate files of different detector spacing, the files with the detector information were edited. Table 3.1 presents a listing of the different detector spacing that was generated. In Mile 1 detector condition, every other detector in the detector file was deleted to create detector spacing of one mile. This generated two replications, where one replication contained the odd numbered detectors and the other replication contained the even numbered detectors. The detector files were then compiled in an Excel file and the travel time statistics were computed for the freeway segments. Table 3.2 shows a part of the Excel file that was generated to compute the travel time error for a certain placement of the detectors. The other detector spacing conditions also generated multiple replications.

To proceed, two notions of travel time for a freeway section were defined: Ground Truth Travel Time (GTTT) and Estimated Travel Time (ETT). Likewise, two travel time sections were defined, one each for freeway sections entering and exiting in the VISSIM model. The difference in the travel times between the two sections represents the GTTT. ETT is calculated indirectly. Travel time for the whole freeway section will be estimated from the travel times of constituent detector 'zones of influence' travel times. The zone of influence of a detector can be defined as half the distance upstream and downstream to the neighboring detector (see Figure 3.2).

Travel time for each zone of influence is estimated from the speed data obtained at the detector location from the VISSIM micro simulation. A key assumption in this calculation was that the speed measured at the point detector was approximately equal to the average speed for the entire Zone of Influence (ZOI). The greater the length of the ZOI, the greater the potential for differences in speeds across the zone. The length of the ZOI is divided by this speed to obtain the travel time value ($TT_i = \frac{ZOI_i}{V_i}$) at each detector location. ETT for the entire freeway section is then obtained by adding individual travel time estimates (TT_i) for all constituent ZOI ($\sum_{i=1}^{n} TT_i$). Finally, the difference in both the ETT and GTTT gives the travel time error ($e = abs(\sum_{i=1}^{n} TT_i - GTTT)$).

3.2 Field Data Analysis

All TMS loop detector speeds were collected from the VISUM-Online (V-On) software, now called PTV Traffic Platform. Description of the speed data extraction methodology has been provided in the first part of the project (*11*). To calculate the ETT for the whole freeway section, the same procedure as detailed above was followed. However, for the GTTT computation, GPS travel time for the freeway section was used. In this method, a GPS device is installed in the vehicle and a driver drives this vehicle according to the "flow of traffic" throughout the study region. While the vehicle is running, the GPS device automatically logs latitude and longitude points and times (*1*). Travel time for the whole freeway section obtained from the GPS device is taken as the GTTT, and the difference in both the ETT and GTTT gives the required travel time error.

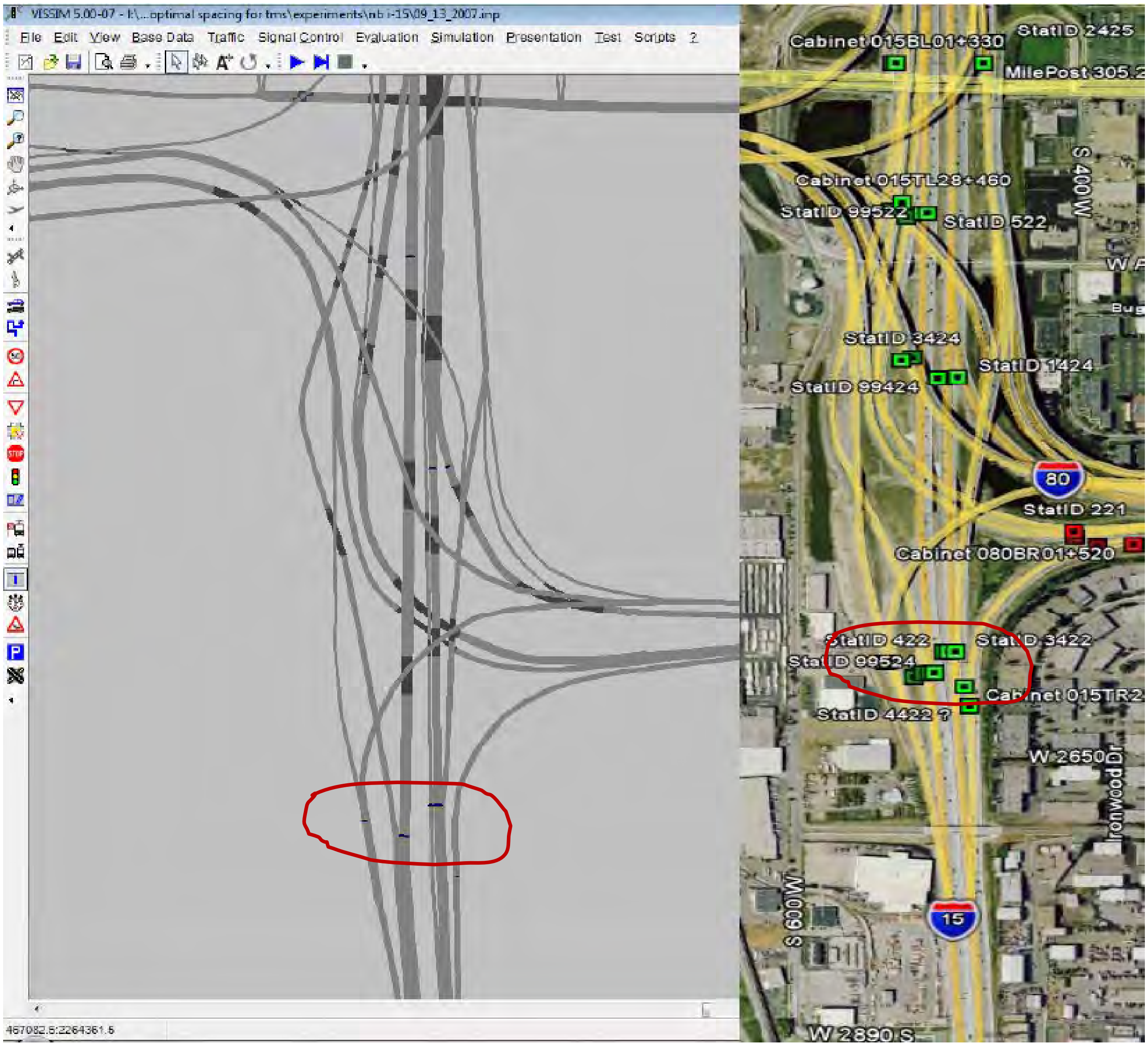


Figure 3.1 Model of a part of I-15 showing built in TMS locations

Table 3.1 Detector spacing conditions generated for the study

Name	Average distance between TMS (miles)	I-15 (800 S in SLC to 400 S in Orem)	
		Replications: No of possible data sets	No of TMS skipped
Baseline	0.5	1	0
Mile 1	1.0	2	1
Mile 1.5	1.5	3	2
Mile 2	2.0	4	3
Mile 2.5	2.5	5	4
Mile 3	3.0	6	5

Table 3.2 Excel table to compute travel time error

Nos.	LOCATION	STATION ID	Data Collection points #	Vissim speed (mph)	Distance (mile)	ZOI	TT(1-1-1)
NB	ALONG I-15	NB	NB	NB	NB	mile	(mins)
		origin					
1	800 S, SLC	88431	4672	68.2	0.004	0.502	0.44164224
2		431	4673	68.2		0.102	0.08973606
3		430	4657, 4658	72.65	0.28	0.24	0.1982106
4	1300 S	428, 1428	4627, 4628, 4629, 4630, 4631	72		0.465	0.38749998
5	1700 S	426, 4425	4603, 4608, 4607, 4606	70.1	0.61	0.63	0.53922966
6	2100 S	424	4017, 4015, 4016	69.7		0.47	0.4045911
7		3422, 422	4005, 4006, 4007, 4008	51.08	0.56	0.445	0.5227095
7		99422	6009	76.1			
8	2700 S	420	4021, 4022, 4023, 4024	69.3		0.48	0.41558442
8		99420	4025	75.9			
9		419	1001, 1002, 1003, 1004	70.05	0.0045	0.202239584	0.1732245
9		99419	1005	74.4			
10		418	4040, 4039, 4038, 4035	69.9		0.222239584	0.19076358
10		99418	4041	74.6			
11		99416	4064	75.9	0.52		
11		416	4065, 4066, 4067, 4068	69.475		0.48	0.4145376

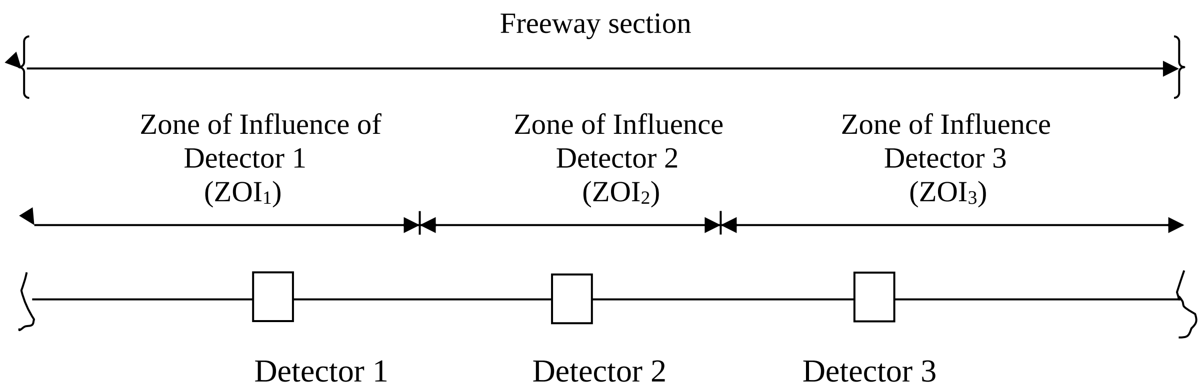


Figure 3.2 Freeway section and zones of influence for detectors

4. RESULTS AND DISCUSSION

4.1 VISSIM Analysis

Table 3 provides the results of the analysis using VISSIM micro simulation speed data for all the generated detector files of different spacing.

Table 4.1 VISSIM results of travel time error for different TMS spacing

Spacing (mile)	No. of TMS	TT error (min)
0.5	57	1.01
1.0	29	0.61
1.0	28	1.93
1.5	19	2.71
1.5	19	3.64
1.5	19	4.14
2.0	15	7.32
2.0	14	4.85
2.0	14	4.47
2.0	14	0.03
2.5	12	3.59
2.5	12	1.62
2.5	11	16.63
2.5	11	2.92
2.5	11	4.51
3.0	10	5.21
3.0	10	2.9
3.0	10	2.6
3.0	9	1.8
3.0	9	15.8
3.0	9	2.12

Figure 4.1 summarizes the same results graphically. Different replications for each detector spacing condition provided different travel time error. However, there exists no systematic pattern in the error value with respect to the spacing. There is no evidence of obvious increase or decrease in the travel time error with the increase or decrease of detector spacing. For the Mile 1 scenario, it was observed that for a certain detector placement, the error value was smaller than the error for the baseline scenario where none of the detectors had been deleted. Similar observation is also noted for the Mile 2 scenario. In addition to examining general trends among replications, the creation of these replications provided a way to study the effect of detector location while controlling for the average detector spacing.

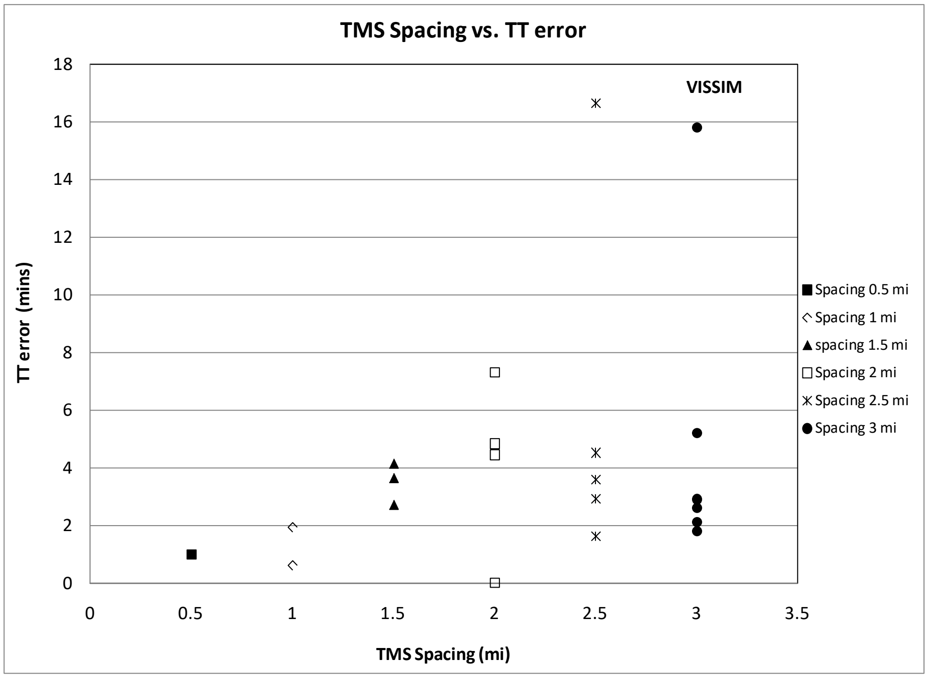


Figure 4.1 Travel time error as a function of TMS spacing

Figure 4.1 provides the relationship between the travel time error and the number of TMS deployed for all replications of different spacing scenarios. Overall, the increase of TMS deployment decreases the travel time error, although there is no general trend of any such increase or decrease of error between individual replications. However, it does appear that 1-mile detector spacing can provide a reasonable estimate of performance measures for tracking congestion.

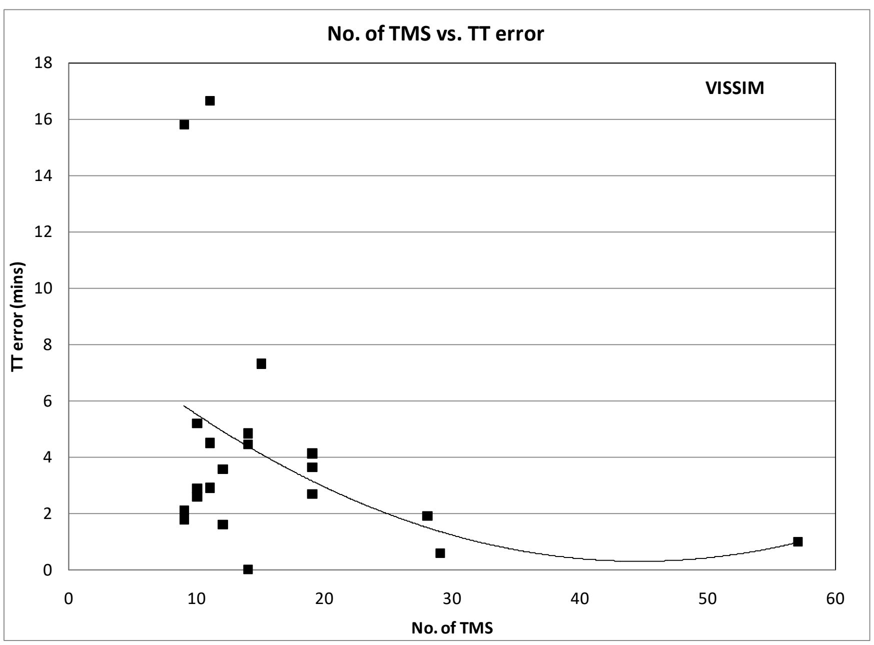


Figure 4.2 Travel time error as a function of No. of TMS deployed

4.2 Field Data Analysis

The results of the data analysis using the field data have been tabulated in Table 4.2. Similar to VISSIM results, there does not appear to be systematic bias in the direction of over- or under-estimation of error as the detector spacing increases relative to the base line condition of 0.5-mile average spacing.

Table 4.2 Field results of travel time error for different TMS spacing

TMS spacing (mile)	No of TMS	TT error (min)
0.5	57	3.44
1.0	29	4.36
1.0	28	1.74
1.5	19	2.73
1.5	19	2.23
1.5	19	5.18
2.0	15	3.15
2.0	14	1.36
2.0	14	5.32
2.0	14	3.11
2.5	12	0.82
2.5	12	3.94
2.5	11	5.08
2.5	11	3.00
2.5	11	2.83
3.0	10	4.01
3.0	10	5.03
3.0	10	2.94
3.0	9	0.60
3.0	9	4.95
3.0	9	2.04

Figure 4.3 summarizes the results graphically. The baseline scenario gives more error than most of the other detector placement scenarios. Figure 4.4 provides the relationship between the travel time error and the number of TMS deployed for all replications of different spacing scenarios. In general, the error value lies withinthe same range for the different detector spacing.

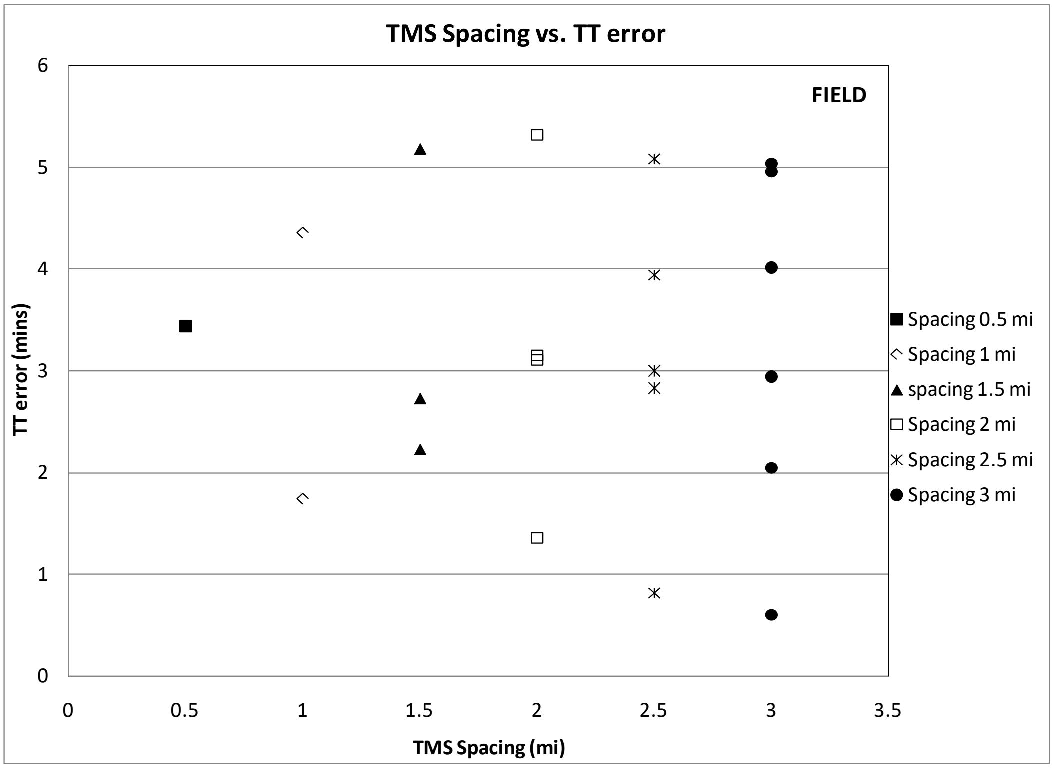


Figure 4.3 Travel time error as a function of TMS spacing

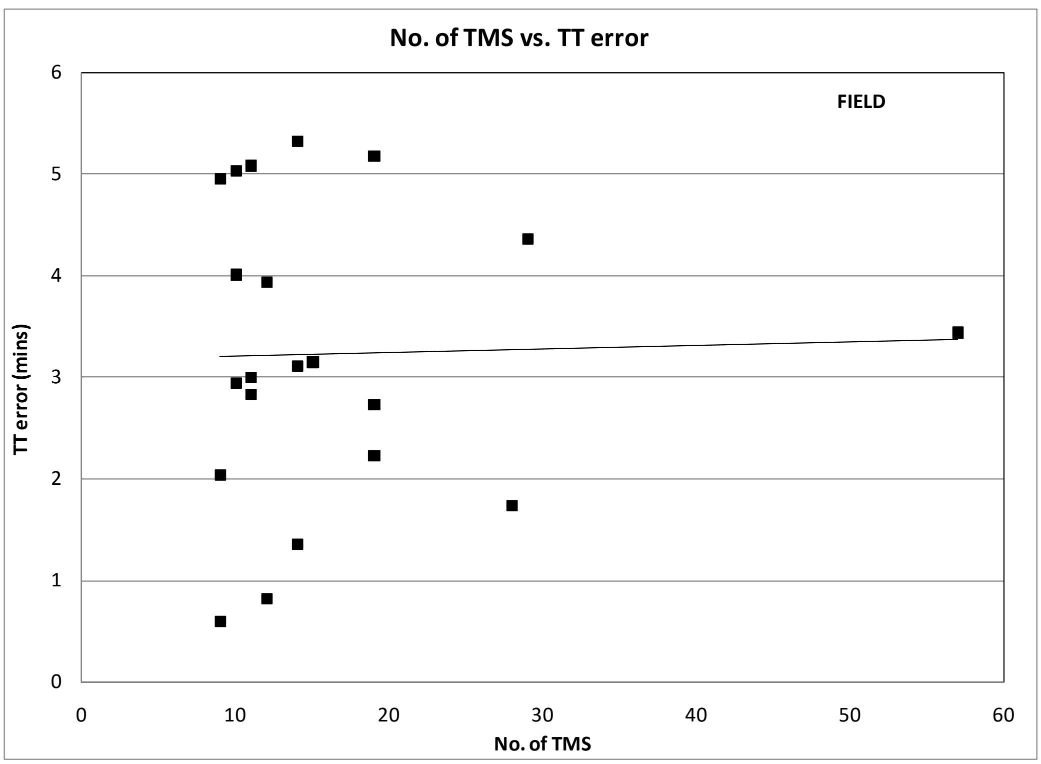


Figure 4.4 Travel time error as a function of No. of TMS deployed

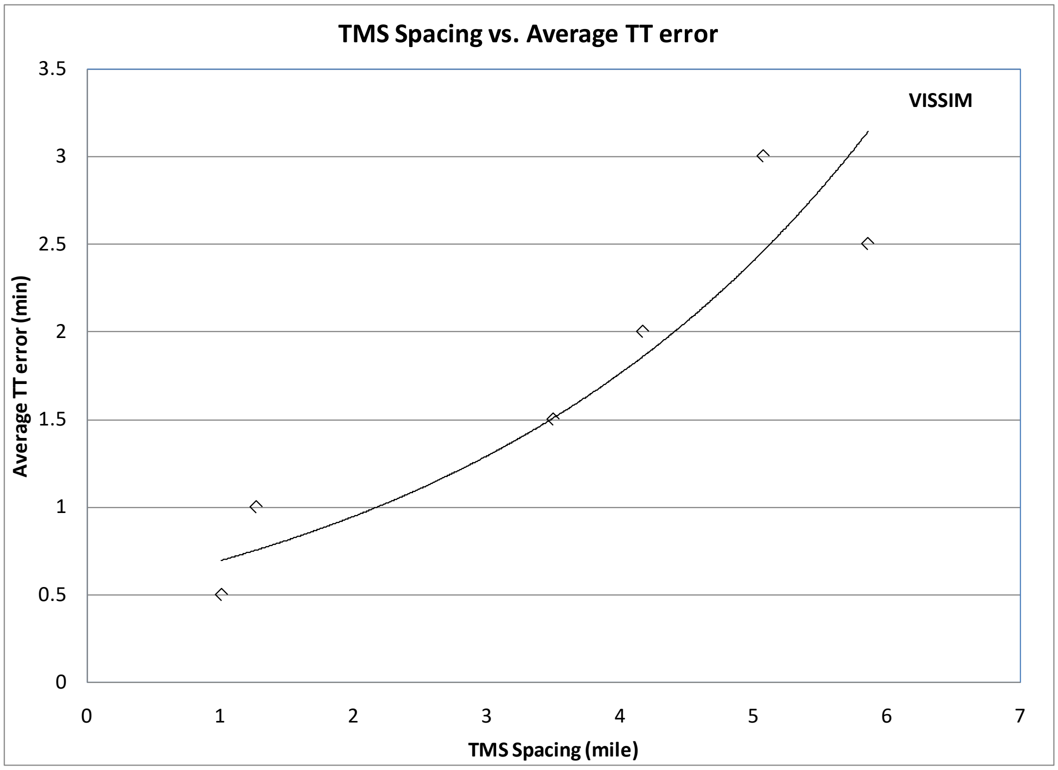
4.3 VISSIM vs. Field Data Analysis

The average travel time error over all the replications of individual spacing cases was compiled in order to facilitate an overall comparison between both the VISSIM and field results. Table 4.3 provides these results for comparison. The VISSIM results show that with an increase in detector spacing the average travel time error gradually increases. However, for the field results, there is no systematic variation. The travel time error value lies within a short range for all detector spacing.

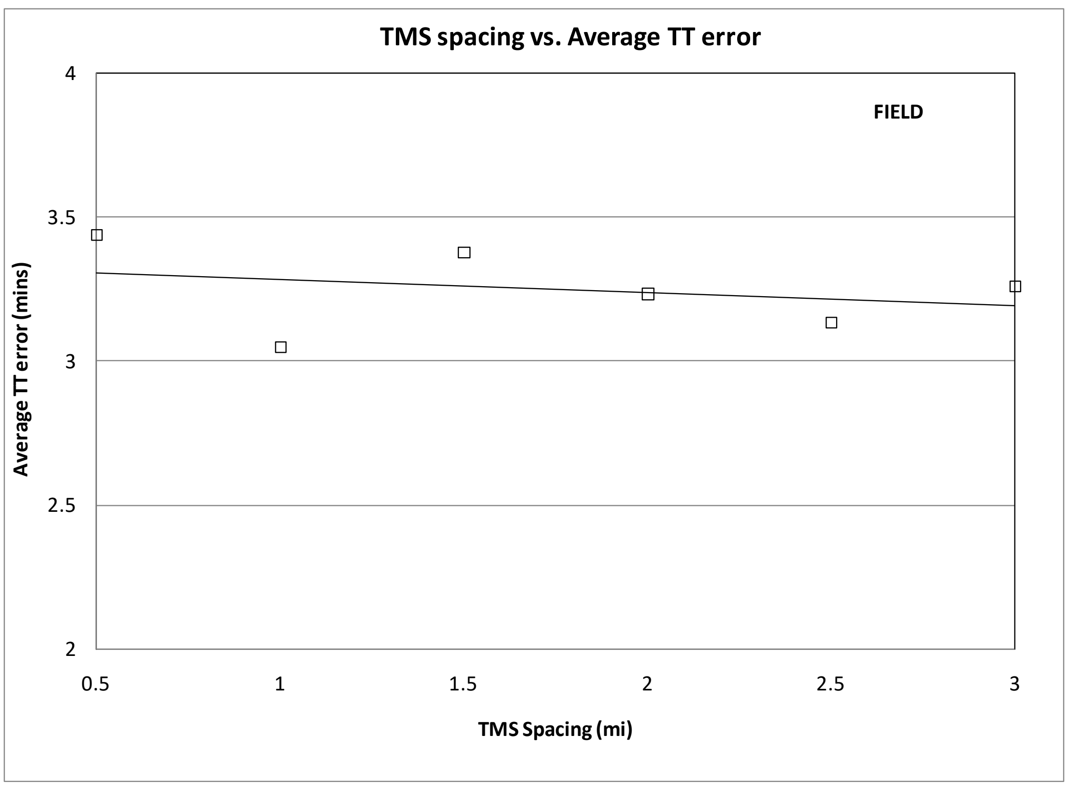
Table 4.3 Comparison between VISSIM and field results

Name	Average distance between TMS (miles)	Replications: No of possible data sets	Average TT error (min)	
			VISSIM	Field
Baseline	0.5	1	1.01	3.44
Mile 1	1.0	2	1.27	3.05
Mile 1.5	1.5	3	3.49	3.38
Mile 2	2.0	4	4.17	3.24
Mile 2.5	2.5	5	5.86	3.13
Mile 3	3.0	6	5.07	3.26

Figure 4.5 provides the trade-off plot between TMS spacing and the average travel time error for both the VISSIM and field results. As noted earlier, VISSIM results show a definite pattern between the average errors with the spacing, however, the field results show no such behavior. Therefore, VISSIM results are in agreement to the general consideration that travel time error increases with the increase in the detector spacing. For the field results there is no definite trend of results, which might be due to the malfunctioning of a large number of detectors producing unreliable and inaccurate detector speed. Detailed analysis and discussion about the reliability of these field detectors are noted in the first part of this project.



(a)



(b)

Figure 4.5 Comparison between VISSIM and field results

4.4 Further Analysis of TMS Location on Travel Time Error

In the previous section, the travel time error produced by different detector spacings was compared. The result indicated that detector spacing has an impact on the travel time error. However, the effect is not systematic in that as detector spacing increases there is not a consistent over- or under-estimation of the error value. Part of the complexity has to do with the actual location of the detectors. Depending on which detectors are "selected," one can obtain a rather different picture for the congestion along the corridor. The results could change if a different detector spacing replication were selected for comparison. However, in the analysis where detector spacing was controlled, the different replications containing different detector locations indicated that different travel time error would result. A replication may contain a detector that is located in a more congested part of the freeway, thereby changing the overall picture of the freeway. Consequently, further analysis was performed by strategically selecting detectors located near merge or diverge and other important locations along the corridor.

VISSIM micro-simulation provided more reliable results than field results, hence, further analysis with strategically selected TMS was continued with the VISSIM data only. The methodology followed to choose the important detector locations is described below.

Looking at the magnitude of the freeway speed data profile and the speed limitation criteria, the congested regions were easily identified. Technically, the regions where travel speed is much lower than the speed limit are the potential locations of congestion. First, we arranged all the speed data on the freeway section in an ascending order of their magnitude. Next, we started our analysis with 10 lowest speed data and applied our objective function using the ZOI concept to compute the travel time error estimate. Then, to the existing 10 detectors we added one more detector, which is next in the ascending speed rank list, and followed the same procedure to compute the minimum travel time error. Similar speed data in the rank list were selected together. This procedure enabled us to analyze the effect of each and every TMS in the freeway section. However, the effect of the random selection of TMS were missing in our approach, which requires the application of the Genetic Algorithm optimization tool.

Figure 4.6 shows the trade-off plot of the travel time error as a function of the number of detectors selected strategically. It can be inferred that deploying 29 TMS would result in the least maximum TT error (~ 0.15 min) and an acceptable eror distribution. In the condition with strategically located detectors, the travel time error varies greatly from the baseline detector spacing condition. In comparison, the strategically located detectors seem to overestimate the travel time error during the peak periods. One reason for this discrepancy may be the average of TT derived from detectors included in baseline spacing condition depresses the actual congestion at merge or diverge locations. Furthermore, the ZOI for some of these selected detectors is larger, so the TT computed over a longer distance may account for some of the differences in the calculation of the TT. The layout of the optimal set of TMS is shown in Figure 4.7. We can conclude that 29 TMS, as opposed to the 57 TMS (baseline condition), are more than is needed to provide reasonably accurate travel time estimates, which significantly reduces the maintenance costs of the TMS detectors.

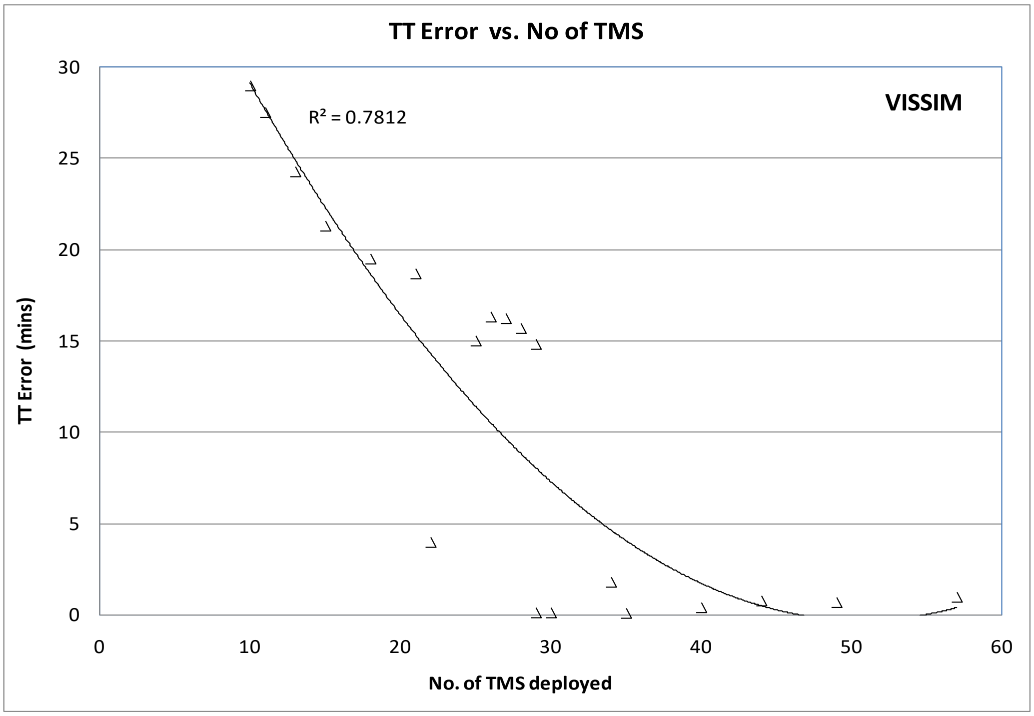


Figure 4.6 Travel time error vs. No. of TMS deployed "strategically"

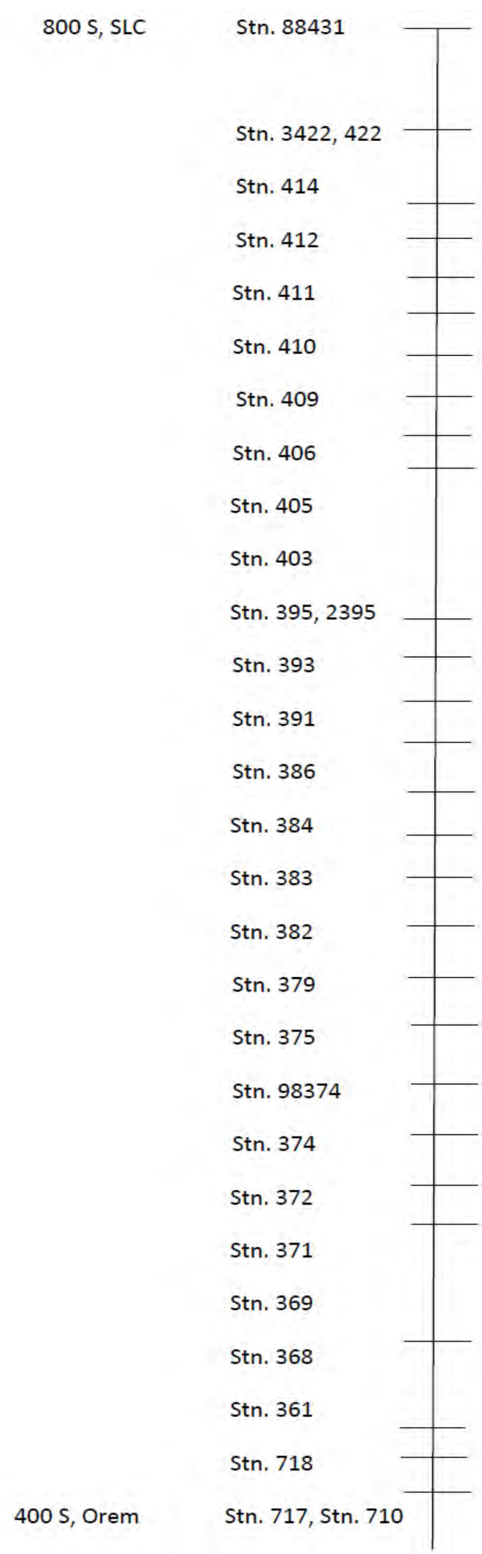


Figure 4.7 Location of the optimal set of TMS for I-15 NB study section (29 TMS)

5. CONCLUSION

The goal of this project was to evaluate the optimal spacing of the traffic monitoring stations considering the trade-off between TMS spacing and accuracy of travel time estimates. This empirical analysis addressed the question “what is the impact of decreasing detector coverage on a freeway corridor on the computation of congestion measure (travel time error)?” The results showed that when detectors were deleted relative to the actual baseline detector spacing, the travel time error varied. Increasing the TMS spacing led to over- or under-estimating travel time error relative to the baseline condition. Evidence that the travel time error became “worse” as more TMS were deleted was not found (e.g., 1 mile vs. 2 miles). Rather, the results varied with TMS spacing and location of the detectors. The analysis showed, as might be expected, that the actual location of the detectors is important in the estimating of TT for the corridor.

Further analysis was conducted where “strategically” selected detectors were included in the computation of travel time error for the corridor. Rather than deleting detectors in a mechanistic or uniform manner (e.g. deleting every other detector or every two detectors, etc.), detectors were selected at points where congestion was expected to occur, such as merging or diverging freeway points. This empirical study illustrates the effect of detector spacing on the calculation of corridor congestion measure, such as travel time error. Selection of specific placement of the detectors is a key element in obtaining valid measures of corridor congestion.

The results presented in this report are premature for recommending how practitioners should prioritize their budgets for repair and maintenance. Comparison of the results with an optimization technique is required in order to ensure robustness. However, the results suggest that more detectors are not necessarily “better,” depending on the usage of the data. It does appear that detector spacing of one mile should provide a reasonable estimate of performance measures for tracking congestion. The actual spacing between two adjacent detectors may be narrower or wider, depending on the freeway geometry. One factor that practitioners should consider is the detector location. Finally, more work on the theoretical underpinnings of this study needs to be done.

6. PROPOSED FUTURE WORK

The efforts on this current research project have resulted in the identification of future research directions. The necessary future work is outlined here as a proposal to extend the current project.

The study on the evaluation of the optimal spacing of the TMS considering the trade-off between detector spacing and travel time error has been completed. The mathematical technique followed in this analysis procedure was based on the objective function ($e = abs(\sum_{i=1}^{n} TT_i - GTTT)$). The outcome of our analysis validates the existing literature on the optimal detector placement problem. However, in order to increase the robustness of the analysis we propose to apply an optimization and heuristic approach to the problem. From the literature review, we have chosen the optimization or search technique to solve this problem. In general, optimization technique searches for an intelligent arrangement of solutions that satisfies the objective criteria. This theory is vitally important for modern engineering and planning that incorporate optimization at every step of the complicated decision making process. Unlike most conventional optimization algorithms, genetic algorithms search from a population of individuals, producing an entire set of solutions as the optimization outcome. We, therefore, propose to use the Genetic Algorithm (GA) tool as the future optimization technique for the optimal detector placement problem. Pareto Optimality will be applied to the solutions of GA to yield the Pareto Optimal trade-off curve. Further, the non-dominated (Pareto) solutions will be mated to find new solutions that would be the optimal ones.

6.1 Genetic Algorithm

A Genetic Algorithm is an optimization technique or search algorithm based on the mechanics of natural selection and Darwin's theory of survival of the fittest (*10*). Here each individual represents a potential solution to a given problem, which evolves through many generations. The generation process is constrained by termination criteria. The searching capability of genetic algorithms is exploited in order to search for an appropriate solution. In GAs, the parameters of the search space are encoded in the form of strings (called chromosomes). A collection of such strings is called a population. Initially, a random population is created, which represents different points in the search space. An objective and fitness function is associated with each string that represents the degree of goodness of the string. Based on the principle of survival of the fittest, a few of the strings are selected and each is assigned a number of copies that go into the mating pool. In general, the natural genetic processes are

- natural selection: the fittest individuals have the best chance to survive & reproduce
- recombination: advantageous traits shuffled to offspring
- inheritance: the offspring inherit genes from their parents
- mutation: random modification (preserves diversity within the population)

In Gas, recombination and inheritance are combined into an operator "crossover." Thus, biologically inspired operators, like crossover and mutation, are applied on the strings to yield a new generation of strings. The process of selection, crossover, and mutation continues for a fixed number of generations or until a termination condition is satisfied.

6.2 Using GA to Optimize Detector Locations

Step 1: Encode the parameter set for the problem as a binary or real number representation.

Step 2: Randomly generate the initial population of P solutions (strings) and evaluate the fitness value (objective function value) for each of these solutions.

Step 3: Select two strings from the current generation (parents) that will participate in reproduction, the selection probability being proportional to the fitness value.

Step 4: Perform Crossover: Parents selected in step 3 are mated by exchanging genetic material to produce two offspring.

Step 5: Perform Mutation: With a very low probability, mutation operator is applied to the newly born offspring.

Step 6: Repeat steps 3, 4, and 5 until P offspring are generated. These offspring constitute the new generation of solutions.

Step 7: Replace the old population of solutions with the newly generated offspring and repeat steps 3 through 7 until a pre-specified number of generations or other convergence criteria is met.

Final solution is the best solution from those discovered during the search. GAs has the ability to arrive at approximate solutions (close to optimal) for complex combinatorial optimization problems. The new generation of solutions, on average is expected to perform better than the parent population because only the good solutions from the parent population are allowed to participate in future mating.

6.3 Pareto Optimality Tradeoff Curve

Pareto optimality, named after Italian economist Vilfredo Pareto (1906), is a measure of efficiency in multi-criteria objectives. The concept generally has wide applicability in economics, game theory, multiobjective optimization, and multi-criteria decision-making. Multi-criteria or Multi-objective problems are those in which there are two or more criteria measured in different units and no agreed upon conversion factor exists to convert all criteria into a single metric.

A solution can be considered Pareto optimal if there is no other solution that performs at least as well on every criteria and strictly better on at least one criteria. A Pareto-optimal solution cannot be improved upon without hurting at least one of the criteria. Solutions that are Pareto-optimal are known as non dominated, non inferior, or Pareto-efficient. A solution is not Pareto-optimal if one criterion can be improved without degrading any others. These solutions are known as dominated or inferior solutions.

Pareto optimality can be visualized in a scatter plot of solutions (Figure 6.1). Each criterion is graphed on a separate axis. In a problem with two criteria, both of which are to be minimized (e.g., optimum number of detectors that give smaller travel time error), Pareto-optimal solutions are those in the scatter plot with no points down and to the left of them. Dominated solutions are those with at least one point down and to the left of them.

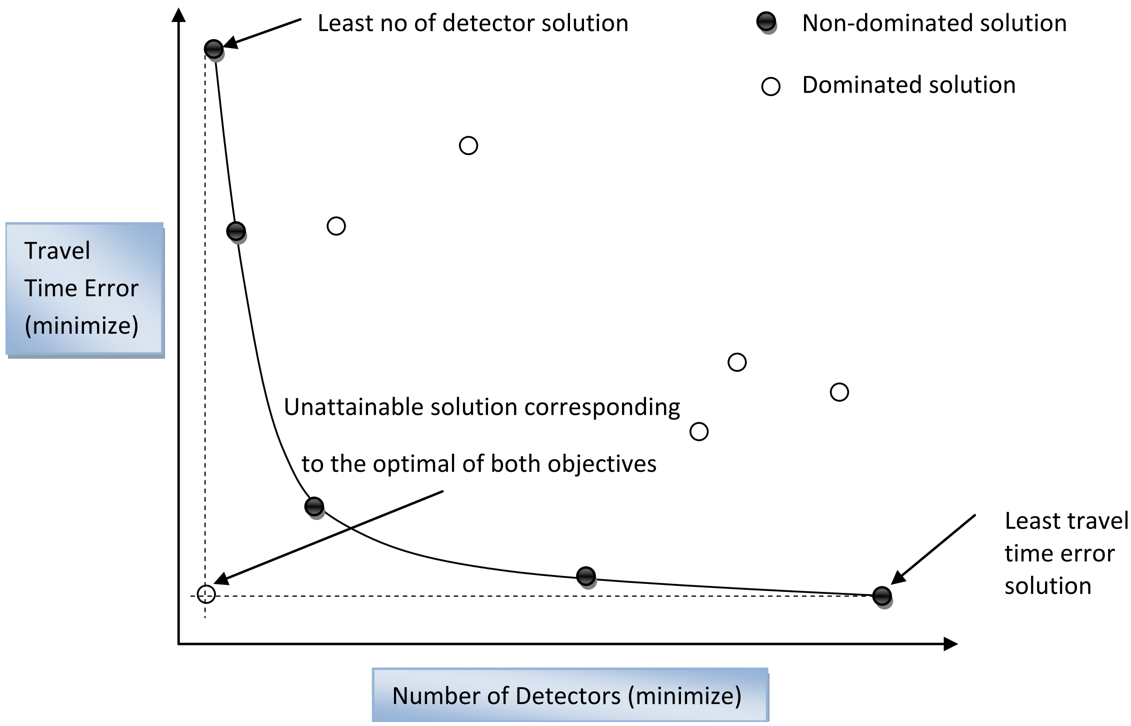


Figure 6.1 Pareto Optimality Trade-off Curve

6.4 Summary

Genetic Algorithm search procedures are designed to locate the global optimum. GAs can maintain a population of solutions, and at the same time search for non dominated solutions. These attributes meet the requirement of seeking a Pareto optimal set in a multi-objective problem. In multi-objective optimization problems via GAs, at each generation the objective or fitness function of each individual is decided accordingly to its non dominated property. Non dominated individuals always have a higher probability of proceeding to the next generation because they have the highest fitness values. As evolution continues, a population converges to its Pareto optimal set (non dominated) zone. Solution points comprise the non dominated individuals in the population and represent a possible Pareto optimal subset, as well as trade-offs among design objectives.

The present research could be extended to the findings for the evaluation of the optimal spacing of the TMS detectors on freeways using the Genetic Algorithm with Pareto optimal search approach in order to find the optimum location of detectors. Figure 6.2 shows the flowchart of the Pareto Genetic Algorithm that would be followed to obtain the optimal detector locations with respect to minimum travel time error. The results of this technique would be helpful in making recommendations on the optimal spacing of the detectors for any freeway section. This would enable practitioners to prioritize their budget for repair and maintenance.

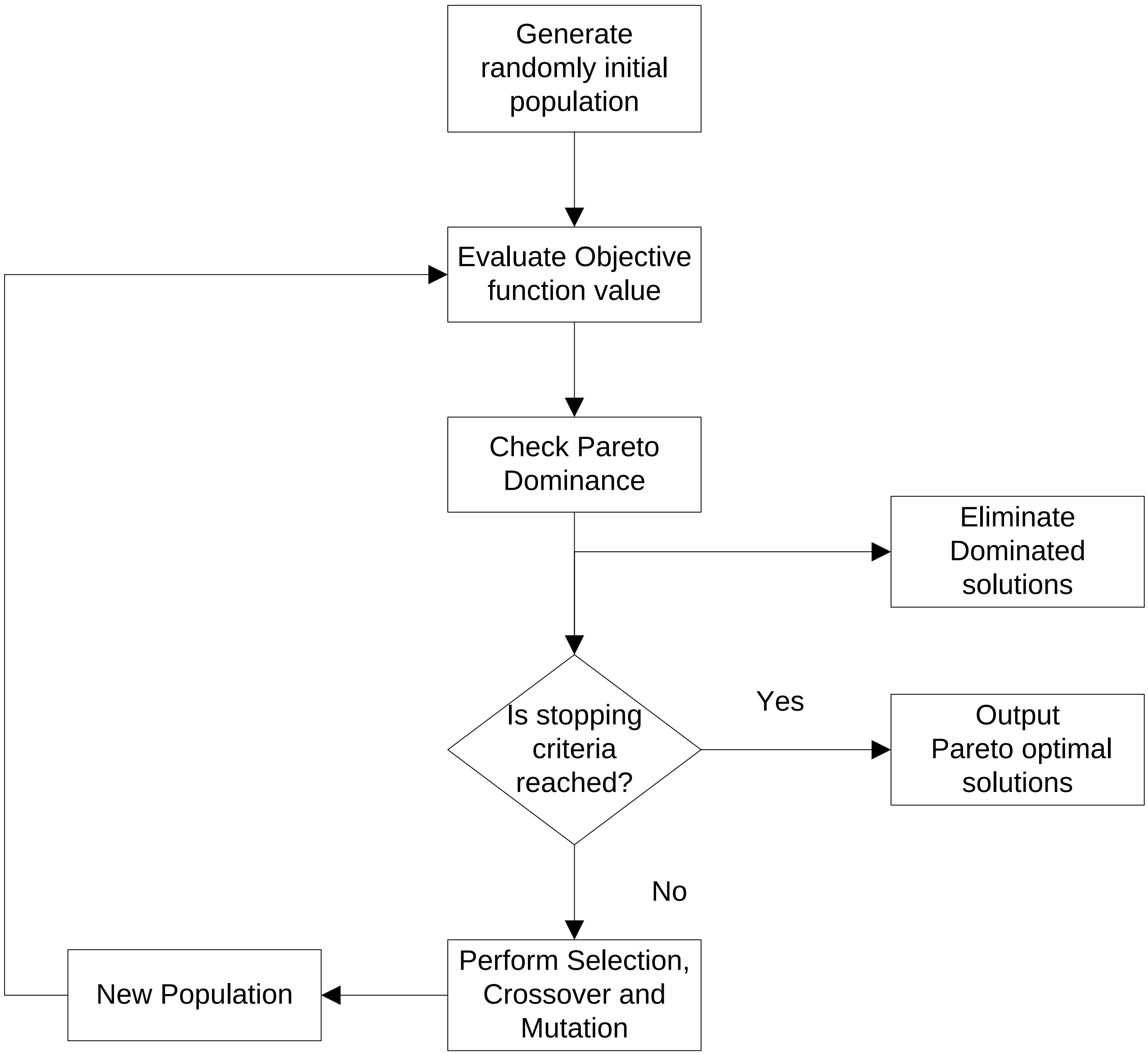


Figure 6.2 Flowchart of Pareto Genetic Algorithm

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