A Real-Time Flow Estimation Model for Advanced Urban Traffic Control

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Executive Summary

This research investigates the performance of the TMERT model with respect to:

- How sensitive is the model to the intensity of detector coverage?
- How sensitive is the model to detector location?
- Will the model perform consistently for various network flow conditions: under-, near-, and -over-saturated conditions?

Locating traffic detectors within a network is currently based on a haphazard method of "gut intuition" or a specific localized need. Adaptive Signal Control Systems do not attempt to optimize the detection need and instead incorporate saturation detection throughout a network. However, the cost of such complete detection coverage renders adaptive signal control an expensive option for most cities.

This research investigates the effects of network congestion, link traffic flow level, detector coverage and link location on estimating network traffic flows using the TMERT model. The research supports a methodology for optimal location theory and the value of planning detection locations for a flow estimation model. The findings allow researchers from many areas to consider model development without the current trend of implied saturation coverage that makes so many of the latest technologies beyond most practitioners resources.

A 20 intersection network located in downtown Salt Lake City, Utah provides the setting for the research testing. A Monte Carlo simulation, based on a week of observed network flow information, is developed to estimate link and turning movement flows and develop the sets of "known" flows. These sets of known flows provide the baseline data to compare the effects of the different strategies used to evaluate the detection placement. This model was validated utilizing observations of cordon and internal link flow detection. The Monte Carlo simulation allows a wide range of flow volumes to be investigated that would normally be difficult and expensive to collect. The simulation also reduces the noise inherent to actual traffic flows. This reduction in traffic noise is important during the development stage so that variations in results from the modeling can be attributed to procedures rather than inherent traffic fluctuations.

While supported with theoretical supposition, the most compelling support for this work is the enumeration process that has investigated over 5,000 TMERT modeling runs for a range of network flows. A systematic evaluation of detecting individual links to determine the impacts of detector location placement on the overall model performance provides a method for determining the relative relation between flow, congestion and link location.

The result is a Utility Function that allows each link in a network to be ranked based on an exponential equation that is a function of link flow and location rating within the network. Based on the results of the investigation, the Utility Function places the average link within 10% of its ranking based on enumeration modeling. Testing various detection patterns, using multiple detectors, supports the Utility Function results. Two primary philosophies are applied to multiple detector pattern evaluation. The internal link detection proved superior to peripheral detection even when the peripheral detected links possess higher flows than the internal links. Under the same net link flows, a dispersed detection pattern is better than localized detection. Increasing the network detection based on flow (from highest link flow to lowest flow) will provide model estimates with an R^2 in the 90th percentile with only 60% detector coverage. If the detectors are located based on an increasing flow pattern (from lowest link flow to highest flow), then 80% detection is required before model estimates reach the 90th percentile.

The general result is that links with higher flows and located internal to the network provide greater insight in solving the flow estimation problem. Although the results are promising, further investigation is needed to evaluate the interaction of internal link detectors and develop a dynamic method of determining the optimal detection pattern based on a known quantity of available detection devices.

There will always be need for traffic detection. However, the purpose, location and method of placement varies for the specific type of detection need from policing red-light violators and speeders, to measuring traffic volumes, to actuating signal demand. This research is not intended, nor does it suppose, that all detection purposes can be located with the developed Utility Function. Instead, the function is a tool for helping transportation engineers locate vehicle detection with the specific application of estimating flows in support of a real-time adaptive control traffic signal system. The research has identified one method for ranking the possible detector locations within the network so that transportation engineers may efficiently utilize the resources available.

1.0 INTRODUCTION

While the need for efficiency improvements exists on all aspects of transportation facilities, this research focuses on urban signalized intersection networks within a city. Specifically presented by this research is an investigation of input support methodology for a flow estimation model (TMERT) that aids adaptive signal control systems.

Timely traffic flow information is critical for both optimizing and efficiently operating a signalized urban network. If the traffic flows on each link of a network are known, then timing plans can be implemented to optimize coordination and effectively reduce delay to vehicles. If turning movements at each intersection are known or accurately estimated, then true optimization can occur. While there exists adaptive control systems that optimize signal timings in real-time, they rely on saturation detection of a network where each link and intersection approach are inundated with multiple detection devices. This causes the cost of these advanced systems to be more expensive than most US cities are willing to invest. This is why only a handful of cities in the US currently operate these adaptive signal systems.
If costs for these adaptive systems were reduced, by eliminating the need for saturation detection, then the systems would become more attractive. The TMERT model provides a mechanism for estimating flows, both unknown link and intersection turning movements, and allows complete flow information to be inferred without the need for saturation coverage.

While automatic vehicle detectors provide link flow measures, costly detection systems are needed to detect turning movement flows. The TMERT model applies State Estimation Theory to network traffic. Linear programming provides the mathematical basis to solving a network optimization problem. By detecting a sample of link flows in real-time, cordon flows and network geometry, unknown link and turning movement flows can be estimated.

The research premise is that the TMERT model can infer traffic flow information sufficiently for use with an adaptive control signal system using less than saturation detection. The optimal layout of detection devices is a function of the number of detectors and the relative location to other detectors with influences due to link flow. There exists an optimal condition where increasing the number of detectors provides a diminishing improvement on modeling quality.

The goal of the research is to develop a methodology for efficiently locating detection units in support of a flow estimation model. This is accomplished by the supporting analysis objectives.

1. Survey of turning proportion variation by small recurring intervals to determine sample size and variation of traffic flows.
2. The TMERT model's performance is evaluated using observed, simulated, and modeled turning proportions on a downtown urban Salt Lake City network of 20 intersections.
3. Cordon and internal link data collection in 15-minute intervals for five days to support the development of a Monte Carlo simulation model.
4. Simulation model using Monte Carlo turning movement proportions to develop multiple sets of "known" flows.
5. Testing and validating of Monte Carlo Simulation.
6. Theoretical and enumeration comparison of detection location/allocation theory for traffic flow estimation using the TMERT Model.
7. Modeling Performance Investigation of:
   A. Range of network congestion as a function of Volume to Capacity ratio (V/C level)
   B. Detector coverage as a function of increasing number of links detected
   C. Detector layout dispersion patterns and location impacts on model performance

The coefficient of determination is the principle MOP and compares the changes in TMERT model results.

The specific application of the research is in support of the TMERT flow estimation model. The TMERT application has been identified by local, state and federal transportation representatives as having a wide range of application from real-time flow estimation to planning and incident rerouting control. The more general application is bridging the gap between state-of-the-art and state-of-the-practice in flow estimation by showing that saturation detection is not necessary. Advanced modeling by practitioners is available as never before due to realistic input requirements being realized.

The research tests the location and allocation of detection devices utilizing a 20-intersection network in downtown Salt Lake City, Utah. Flow impacts are evaluated with the TMERT model as the principle tool. In order to minimize the effects of network noise and other traffic discrepancies, simulated data is developed and applied in the testing. This simulated data is from a Monte Carlo model developed specifically to provide sets of “known flows” to test the TMERT model runs. By developing a simulation model in developing the known flows, the traffic noise can be controlled, a balanced network is utilized, and other external factors can be eliminated that impact the results and reduce the reliability of the conclusions. Further, the range of network flow levels can be varied to provide a complete evaluation of traffic congestion effects on the results. When field data is utilized, the flow condition is subject to the time collected and is difficult to obtain the complete range of network flow conditions.

The Monte Carlo and TMERT modeling are separate efforts. The Monte Carlo model is based on field observations. A week of observed cordon and internal link flows collected in 15-minute intervals provided the basis for determining the relationship between link and relative flows in developing the simulated data. Turning movement variation is investigated for four of the network intersections to provide more thorough insight into the turning movement variability issues. These same four intersections are observed for three different PM peak periods on consecutive weeks. Finally, each intersection of the 20-intersection network is observed for approximately 20 cycles to evaluate turning movement flows and proportions of each approach during the peak PM period. This information is applied to the Monte Carlo modeling to determine realistic volumes. The collected link and cordon flows are used to validate that the Monte Carlo model provides realistic traffic flows for the various levels of congestion developed.

Once the simulated flows are completed, sets of “known” flows are available for comparison with the modeled turning movements. A proportion of the “known” link flows will serve as the detected link flows for input into the TMERT model. The testing of the TMERT model’s performance is assessed through a correlation measure, R^2, comparing the “known” and modeled turning movements and link flows.

Several parameters effect the model’s performance and operation. Network size, traffic flow levels, detector coverage, and detector layout pattern all influence the model’s ability to estimate turning proportions and link flows. The following is a discussion of the variable parameters and explains how their impact of the modeling will be investigated.

The stage report documents the purpose and potential uses for TMERT with a detailed discussion of:

- the literature available on turning movement estimation models,
- how the TMERT model has been developed from the scientific field of Operational Research
- The testing and performance of the TMERT model

It then describes the cursory research work of

- Defining a downtown Salt Lake City Network

- Collecting traffic data on the network cordon and turning movements
- Developing a Monte Carlo model to estimate flows on the network so a wide flow range could be investigated
- Testing the Monte Carlo model using the Cordon, internal and turning movement flow information available

Appendix A shows the results of this preliminary flow simulation. Having laid the groundwork for the investigation, this final report continues with the theoretical, empirical testing and finally the conclusions for implementing detection within a network in support of the TMERT model.

2.0 THEORETICAL COMPARISONS

The following is a discussion of a mathematical representation on how the optimizing of detector location and coverage may be implemented. This theoretical representation is then assessed with a numeric approach. In locating the detector position within a network, critical links must be identified. One method is using an O-D matrix where each link use, with respect to the network's available paths, can be identified as a weighed likelihood in use occurrence. However, this is based on assigned traffic and therefore assumes where each vehicle is generated and destined is accurately known. It has already been discussed that the accuracy of these estimates is questionable. When detecting flow, it is unclear where the origin or destination is for the vehicles passing a detector location. Beginning with a defined network, only the cordon loads provide information. As vehicles progress into the network, further from the cordon detectors, the turning movements and flows become more unpredictable.

2.1 Location Puzzle

Considering the input data for TMERT, only the cordon and detected internal links vary over time. With only the cordon flows detected, the network can be represented as Figure 2-1. The network can be characterized as a mathematically balanced jigsaw puzzle. The cordon provides the bounds on entry and exits flows while the internal flows provide insight into the overall network picture. As internal detection devices are added, the puzzle begins to clarify. As with a puzzle, each piece often represents a similar proportional size of the network, but some pieces provide more insight than other pieces. Assuming a given number of detection devices, different placement patterns will produce different results to the modeling puzzle. A concentration of detectors allows a small portion of the network to be well understood, but at the expense of the other larger portion of the network. Detector dispersion provides less complete information on a larger portion of the network. The unknown links between the detected links and cordon loads are inferred. When there are larger link gaps between the detected flows, then the estimates are based on more remote data with less constraints that leads to a less informed estimate. Based on this premise, a uniform distribution in locating detection units provides the optimal overall location policy.

Figure 2-2 shows that if the increase in detection is along the perimeter of the network, we only expand the border's understanding but obtain little information regarding the central network location. The perimeter is also the larger area, so more detection is required to completely identify the area. In Figure 2-2, detecting the approaches to 14 intersections is necessary to fully identify the cordon intersections. In Figure 2-3, the internal intersections are identified by measuring the approaches to just 6 intersections. Detecting the perimeter intersections will always require more detection devices because of the increased intersections along the perimeter border. While more detection requires less inference, the border detection may not provide additional substantial information from the cordon flows alone. As the detection is moved to the center of the network, the puzzle pieces begin to provide more important information.

2.2 Flow Influence

Location is not the only factor that influences detector placement. Each piece of this network puzzle also contains flow information. Knowing the flow on a link provides insight as to where the known external cordon flow is internally. Although it does not provide where the flow originates or where it travels, the value is in knowing the flow associated with different portions of the network. While each link provides a single constraint mathematically to solving the flow estimation problem, higher flows provide more insight by being a larger proportion of the total network flow. Therefore knowing where large flows are, help to determine where smaller flows are likely to occur.

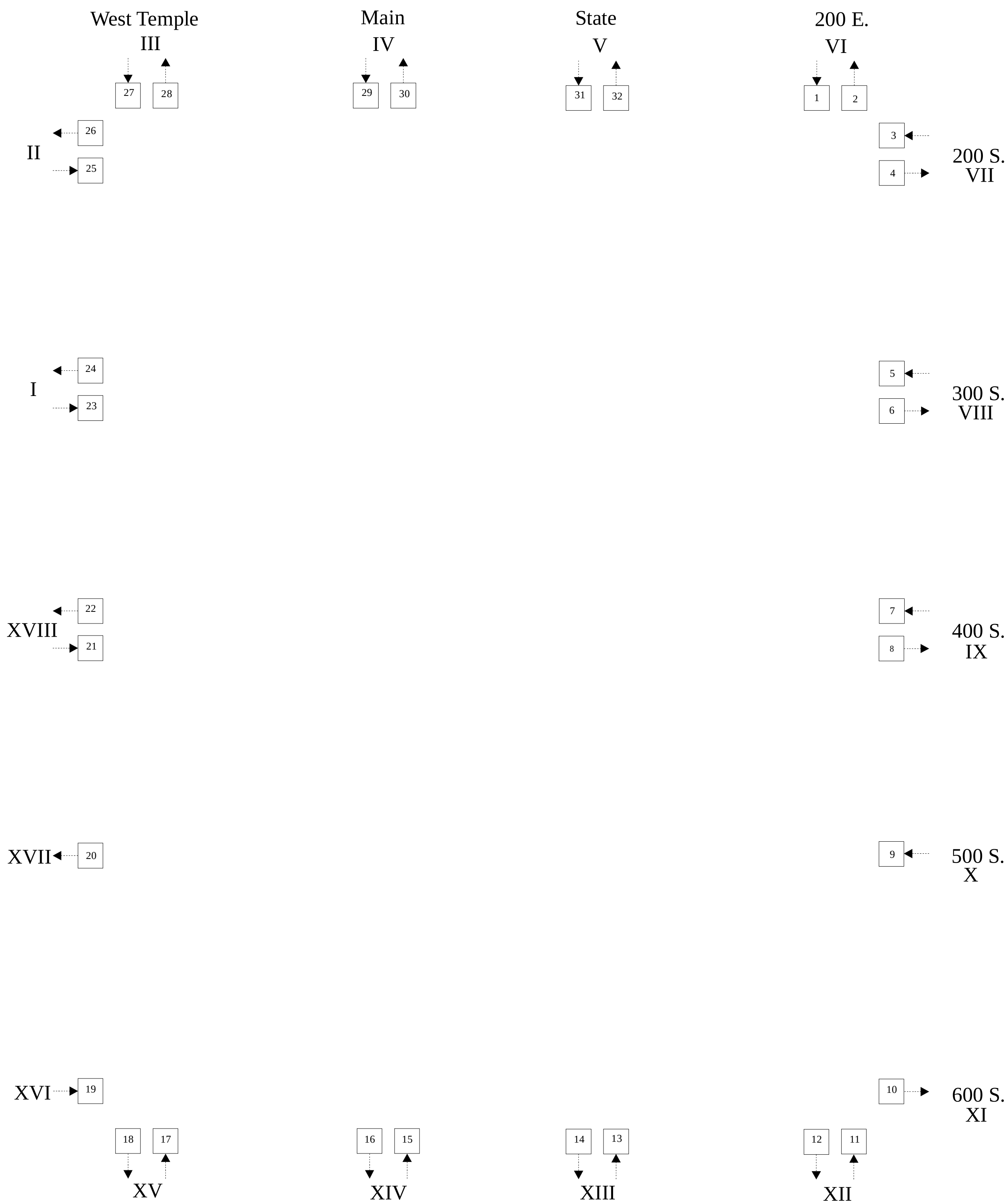


Figure 2-1. Cordon Detection

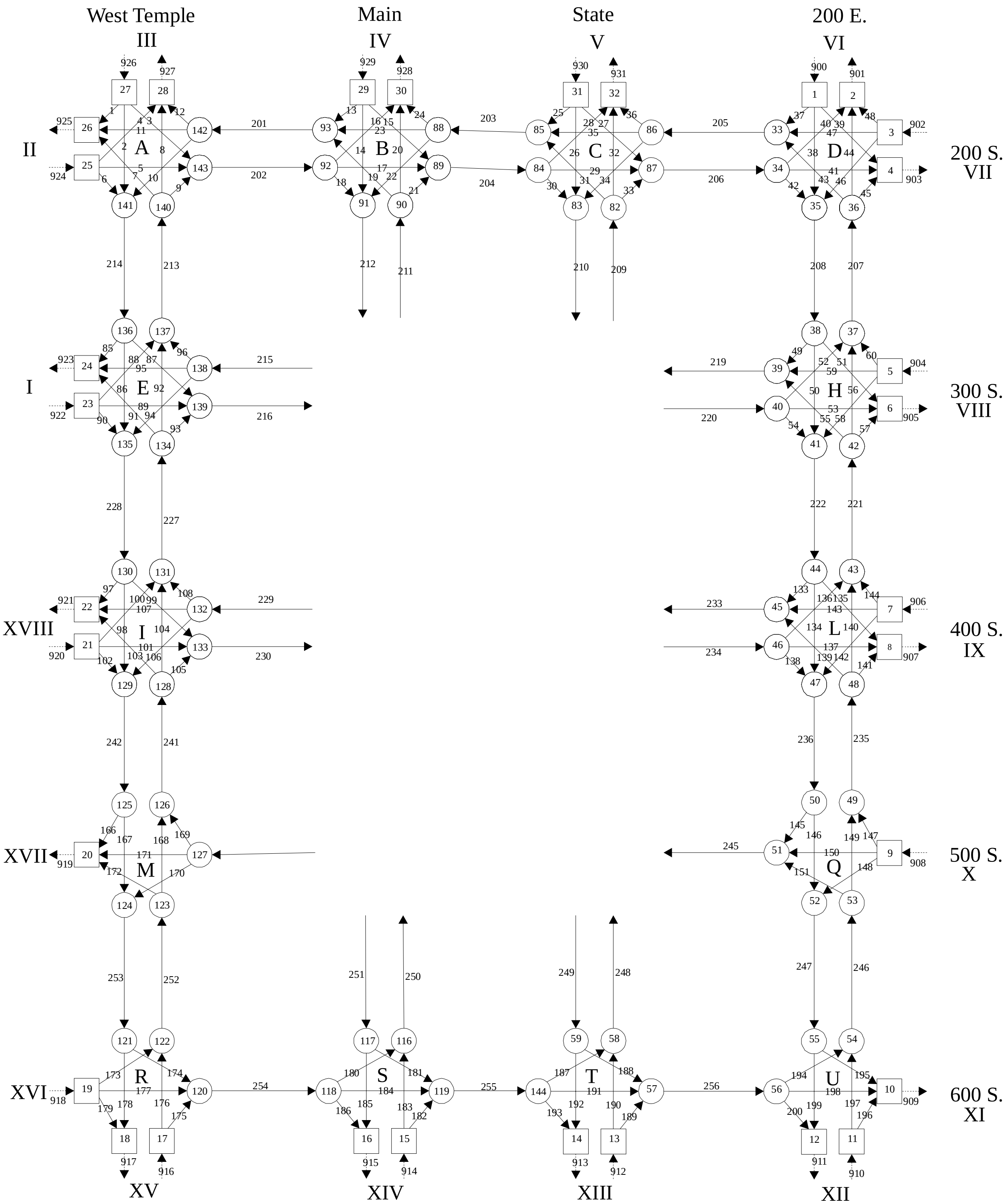


Figure 2-2. Border Located Detection

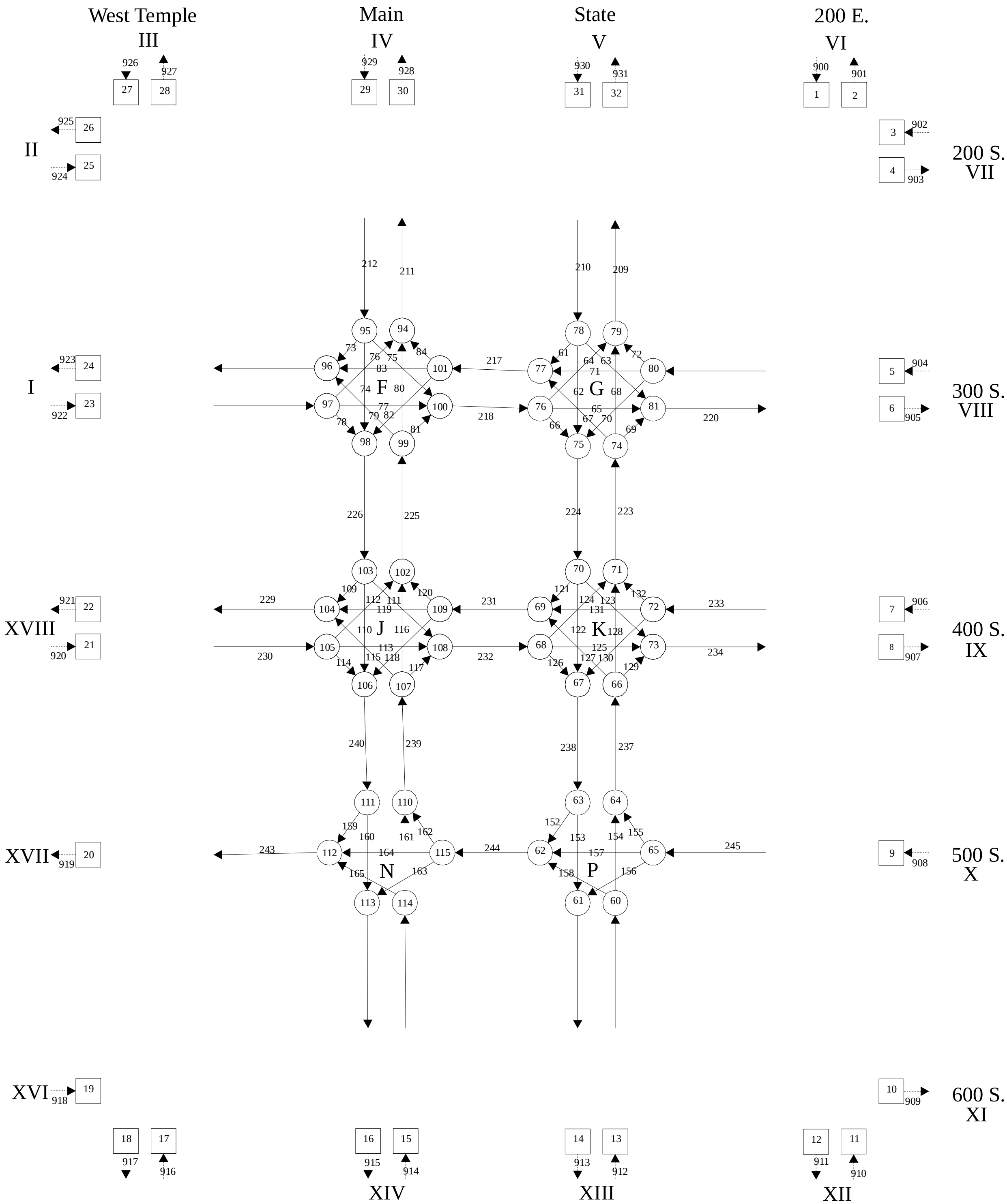


Figure 2-3. Central Located Detection

2.3 Allocation-Location Utility Function

The placement of detection is therefore based on two factors; location and link flow. The placement optimizing can be expressed as a utility function where each potential location is evaluated and a rating determined. The utility function for the traffic detector location problem can be formulated as an Expected Utility (EU). Reckhow (1994) suggested a method for comparing particular projects. The Expected Utility is a function of the utility measure, the weight or cost assigned to the alternative, and the estimated probability of success. Equation 2-1 summarizes the relationship and allows multiple attributes to be incorporated by utilizing a summation factor. There are other methods for ranking proposed actions (Von Winterfield and Edwards, 1986).

$$EU(a_j) = \sum_{i=1}^{k} p_i w_i U_i(x_i)$$

Eq. 2-1

where:

EU = Expected Utility

a_j = evaluated project j

$U_i(x_i)$ = a utility measure for the i^{th} attribute

w_i = a weight on the i^{th} attribute

p_i = is the estimated probability that the expected results (x) will occur for the i^{th} attribute

The approach is adapted to include budget concerns and a multivariate utility function. The solution to the problem of locating and allocating traffic detectors can be approached from two concepts, budgetary and optimization. Optimal design would discount budgetary concerns and the detector placement would continue until a point of diminishing returns was reached whereby the increase in detection units no longer increased the model performance above a minimum standard. Reality is that the budget restrictions of each city, county, and state determines the number of detectors that can be built, maintained and operated within a network and therefore a limitation is placed on the detector number. This limitation can produce a sub-optimal number of detectors whereby each additional detector would improve the model performance above the minimum threshold, however no additional detectors are available. Under the budgetary limitation, detection placement must consider the limited detector number when placing them to ensure that their interaction provides the optimal model performance for the available input.

The budgetary limitation is expressed as a not-to-exceed amount whereby multiple detection types with various costs can be considered. Equation 2-2 describes a method for determining the available detection devices based on the available budget.

$$B \geq \sum_{i=1}^{k} c_i n_i$$

Eq. 2-2

where:

B = budget for Traffic detectors

i to k = the number of different traffic detector types

c_i = cost of detector type i

n_i = number of detector type i

Solving for "n" in Equation 2-2 provides an upper limit on the detector number to be placed. Forming the allocation-location problem into a utility function, two variables are incorporated into determining the relative value of placing a detection unit on each link.

- The traffic flow associated with the link
- The links location within the network.

The influence of flow and location may not be balanced on their relative contribution to the utility value, so a weighting factor is introduced. Equation 2-3 identifies the utility function. In this way, each link is assigned a Utility value to rank the potential detector locations.

$$U_i = k_1 y_i + k_2 z_i$$

Eq. 2-3

where:

U = utility value for location i

i = link locations throughout the network

k_1 = utility weight assigned to the flow contribution to the utility function

y_i = flow relation for link i

k_2 = utility weight assigned to the location contribution to the utility function

z_i = location factor relation for link i

The location factor could be further refined into a dynamic function that incorporates the locations of other detectors as new detector locations are added. The dynamic function of locations may be influenced by its relative position from the static cordon detection devices. As new detectors are added internally to the network, the relative optimal location of the additional detectors may also be influenced by the existing internal detectors. Equation 2-4 describes the dynamic approach to the location factor, z.

$$z_i = k_3 s_i + k_4 t_i$$

Eq. 2-4

where:

k_3 = Utility weight assigned to relative location factor to adjacent internal detectors

k_4 = Utility weight assigned to network location factor based on location from cordon detectors

s_i = Relative location factor to adjacent internal detectors

t_i = Network location factor based on location from cordon detectors

This dynamic utility assignment is not included in the research analysis but does offer an interesting future direction for the work to proceed. Instead, this research concentrates on exploring Equation 2-3 and identifying the influences of traffic flow and network location relative to the cordon loads.

2.4 Theoretical Summary

A weighed function incorporating traffic flow and location within the network provides a utility function is developed for ranking each potential detector location. The theoretical methodology discussed provides a systematic approach and could easily be incorporated into an expert system to allow engineers to determine the value of adding detection units to a network and the resultant impact to their budgets.

While the theoretical development of this approach is important, this is essentially a validation process in which the theory supports the numerical or empirical way in which the investigation is developed. Many of the research oriented transportation modeling and optimization approaches utilize heavily the mathematical and statistical realms to support and develop hypothesized theoretical relationships in traffic. However, the majority of the practiced transportation engineering used by consultants and public agencies relies on empirical relationships. The empirical relationships have always been held as the principal importance with mathematical relationships being developed from the empirical data. An enumeration method for investigating the theoretical approach is described in the following sections.

3.0 ANALYSIS

While often thought of as inefficient and tedious, enumeration is comparing the value of feasible solutions to all other feasible solutions or evaluating all possible combinations. When investigating where and how many detectors should be placed, even trivial networks have many possible combinations. The enumeration process can become taxing if additional constraints, such as bounding, are not used to reduce the combinations evaluated. The value of enumeration is through providing the type of investigation support that practitioners in transportation value over mathematical or statistical relationships. The rift between state-of-the-art and state-of-the-practice is often characterized by the view held by many practitioners that researchers operate in isolation with little understanding for the real traffic environment. This idea is best supported by noting what references are used daily by practitioners as standard transportation guides. The Highway Capacity Manual (HCM, 1994) and the AASHTO Green Book (AASHTO, 1994). While both are available in electronic form so that calculation efficiency is improved, the principles of both references are based on empirically observed evidence.

Many statisticians, physicists, and mathematicians have entered the research field in transportation due to increased funding following the 1991 ISTEA and 1998 NEXTEA reauthorization which has put billions into the transportation community. However, practicing transportation engineers are, and will likely continue, to remain skeptical of ideas that have not been supported by empirical evidence from the streets. The following discusses the method of enumeration investigation for detector number and location whereby the Salt Lake City network of 20 intersection connected by 56 links with 18 cordon locations is utilized. The investigation evaluates the following in order to evaluate the effects of various detector locations, placement strategies and flow regime impacts.

- Detector location in the network
- Flow volume impacts
- Network Congestion levels
- Model Performance as a function of detector coverage

This enumeration method combines the cordon, internal link and turning movement traffic information with the Monte Carlo Model and turning movement variability investigation. The enumeration investigates how sensitive the TMERT model is to the location and allocation of traffic detection location and coverage. While the TMERT model is used for the investigation, the findings are more broadly insightful by indicating the relation between model performance and less than saturation coverage. This provides the catalyst to indicate to technicians that existing and future models should consider the detection requirements in developing the model, moving away from the standard saturation detection methodology. By reducing the need for expensive saturation detection, these new modeling applications will become more attractive to practitioners, both private and public.

3.1 Performance Measures

Throughout the modeling, the principle statistical measure is the coefficient of determination (R^2). With a plot of estimated flows against observed flow a perfect correlation is represented by a R^2

of 100%. No correlation is represented by a R^2 of 0%. The coefficient of determination measures the deviation from a perfect correlation. The coefficient of determination method benefits includes a simple measure range between 0% and 100%. A weakness of the coefficient of determination approach is that large data pairs with good fit can skew the results. This should not become a problem because the results are applied to comparison analysis indicating the improvement in model performance however; no attempt by this research is made to imply the overall TMERT modeling capabilities. The following notation applies to the performance measure:

N, is the number of turning movement flows estimated

s_{rt}, is the actual turning movement or link flow (for flow maneuver *n*, scenario *r*, in time *t*)

d_{rt}, is the turning movement or link flow estimate (for turning maneuver *n*, scenario *r*, in time t)

The Coefficient of Determination (R^2) is given by:

$$R^2 = \frac{\left[\left(N\left(\sum s_{rt} d_{rt}\right) - \left(\sum s_{rt}\right)\left(\sum d_{rt}\right)\right)\right]^2}{\left[N\sum s_{rt}{}^2 - \left(\sum s_{rt}\right)^2\right]\left[N\sum d_{rt}{}^2 - \left(\sum d_{rt}\right)^2\right]} \quad \text{Eq. 3-1}$$

3.2 Individual Link Modeling

The initial investigation systematically detects one link at a time moving throughout the network until all links are evaluated. The enumeration process begins with identifying the effects of detection on each link independent of other links. The systematic method of detecting each individual link is a base line approach in which the general relationship of each link can be related to the overall performance of the model. With only a single detector input, the model output in terms of performance is poor; however, trends can be identified which support how location and flow level effect the model. It is important to understand two factors (flow level and location) are being investigated and considerable effort must be applied so they are evaluated individually without influences from the other. By systematically proceeding throughout the network and only considering one link at a time, the degree of coverage concern is eliminated for the preliminary efforts. However, separating the flow level and location is not easily accomplished.

Using the 70 known flow sets, TMERT modeling runs for each V/C range provide a measure of the single detectors location on the model's ability to estimate flows. The same 70 known set allows each detector location to be compared for its impact on the modeling performance.

While there are 56 links on the SLC network, only 31 sets of detector patterns are evaluated due to the characteristics of the network. The 56 links are modeled as directional components, however, when a detector is installed, the need for communication and power allows both directions to be detected. In practice, it is unlikely that only one direction of travel would be detected if the trouble has been taken to provide power and communication to an area. Therefore, the detectors are assumed to be paired detection where applicable. Due to limited one-way facilities in the SLC network, the detection pairs are not simply half of the 56 links, and 31 independent detection locations are modeled. The results of the modeling is 2,170 TMERT runs (10 runs per V/C * 7 V/C ranges * 31 locations). Figure 3-1 develops the flowchart for the modeling process. Table 3-1 identifies the average performance for each detected link over the 10 runs for each V/C ratio.

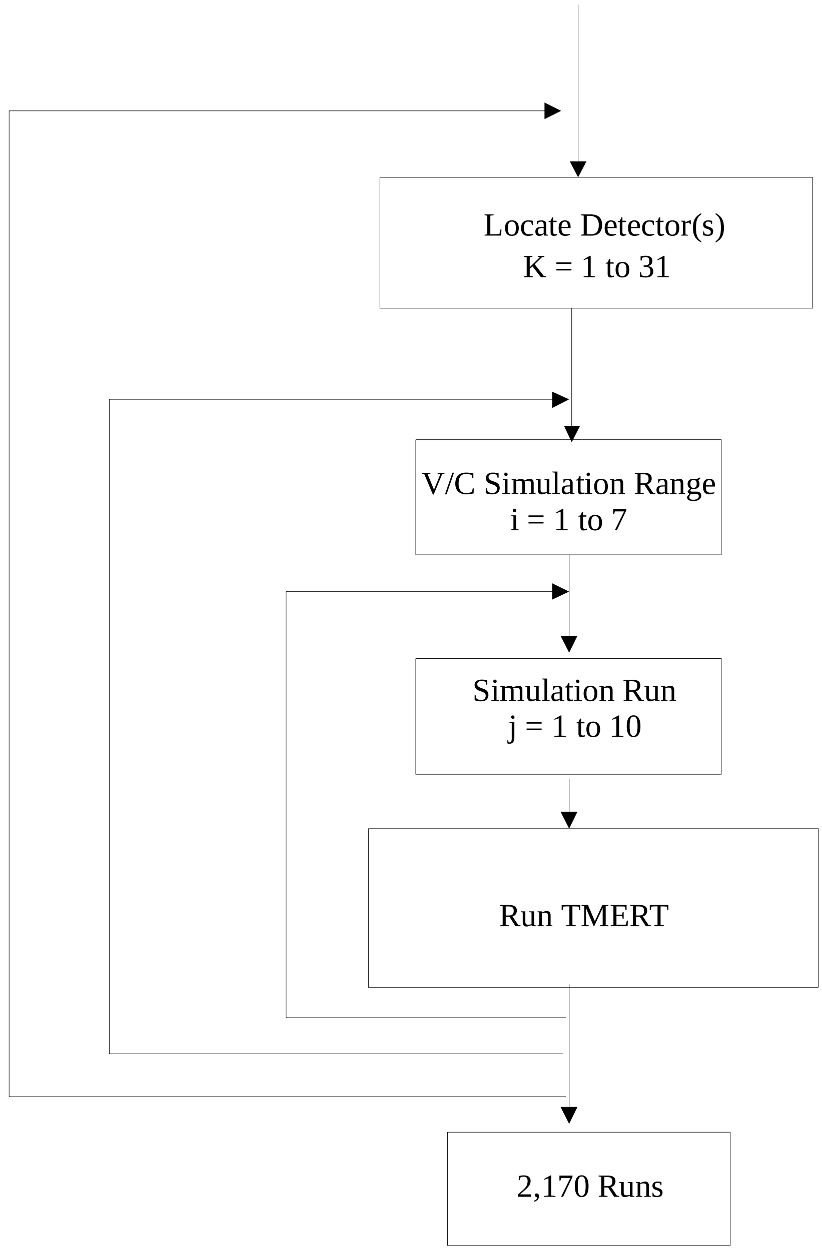


Figure 3-1. Individual Link Modeling

Table 3-1. Average Individual Link Performance by V/C

Avg. of 10 R^2	V/C = 0.5	V/C = 0.6	V/C = 0.7	V/C = 0.8	V/C = 0.9	V/C = 1.0	V/C = 1.1
A-B	23.8	20.0	31.8	32.5	31.0	34.9	49.2
B-C	24.6	20.4	32.1	31.9	30.6	34.0	49.7
C-D	23.5	19.2	32.5	30.4	30.9	34.7	51.3
A-E	23.8	20.0	30.3	31.0	30.3	34.0	45.4
B-F	22.1	17.8	29.9	27.5	27.4	30.3	45.0
C-G	24.2	22.3	32.5	33.0	34.8	38.2	53.3
D-H	19.3	17.2	30.0	28.1	30.9	33.3	47.0
E-F	22.8	19.0	31.3	30.1	30.3	33.9	48.5
F-G	23.8	18.9	30.4	29.5	32.0	35.1	48.8
G-H	21.8	17.6	31.2	30.6	31.9	35.8	50.2
E-I	22.3	19.3	29.4	30.7	33.0	39.7	49.2
F-J	21.6	17.3	27.7	28.7	28.0	27.7	45.4
G-K	33.1	33.0	40.0	39.2	43.3	40.0	50.0
H-L	21.0	18.2	27.1	29.4	30.9	30.1	42.5
I-J	35.2	33.2	41.1	42.9	41.6	42.6	50.8
J-K	35.2	32.7	40.6	43.2	42.1	43.1	50.6
K-L	34.8	32.8	40.6	43.6	42.9	44.9	49.6
I-M	28.8	24.5	32.5	34.4	32.8	35.5	44.5
J-N	21.1	17.6	30.5	28.6	29.0	30.5	44.8
K-P	35.1	32.4	36.9	39.3	42.2	40.6	48.5
L-Q	30.9	30.4	37.2	38.7	37.4	36.3	45.9
Q-P	38.3	36.1	41.7	43.5	41.6	41.8	48.1
P-N	40.2	36.1	43.1	44.0	42.3	42.7	48.8
N-M	40.5	36.6	42.6	44.2	41.9	42.5	49.1
M-R	38.8	31.2	41.1	41.7	42.2	42.7	50.5
N-S	25.4	23.7	33.7	33.8	33.6	33.1	46.0
P-T	33.1	28.4	40.7	39.2	40.3	40.5	49.3
Q-U	29.4	22.6	36.1	33.8	34.7	35.5	45.2
R-S	34.8	26.3	37.5	32.5	32.5	36.0	45.6
S-T	37.4	29.9	40.1	32.7	34.4	36.5	45.0
T-U	27.2	20.9	32.8	31.3	31.4	32.5	44.9

If the averages by V/C in Table 3-1 are plotted, as shown in Figures 3-2, it is observed that the centrally located and higher volume roadways are producing higher R^2 modeling values. Figure 3-2 represents a V/C of 0.5. Plots for the other V/C ranges are available in Appendix B. The values in Figure 3-2 and Appendix B support the discussion of Section 2 identifying the detector location as a function of roadway flows and network location. The subsequent need is to isolate the location and flow impacts in order to calibrate the hypothesized utility function of equation 2-3.

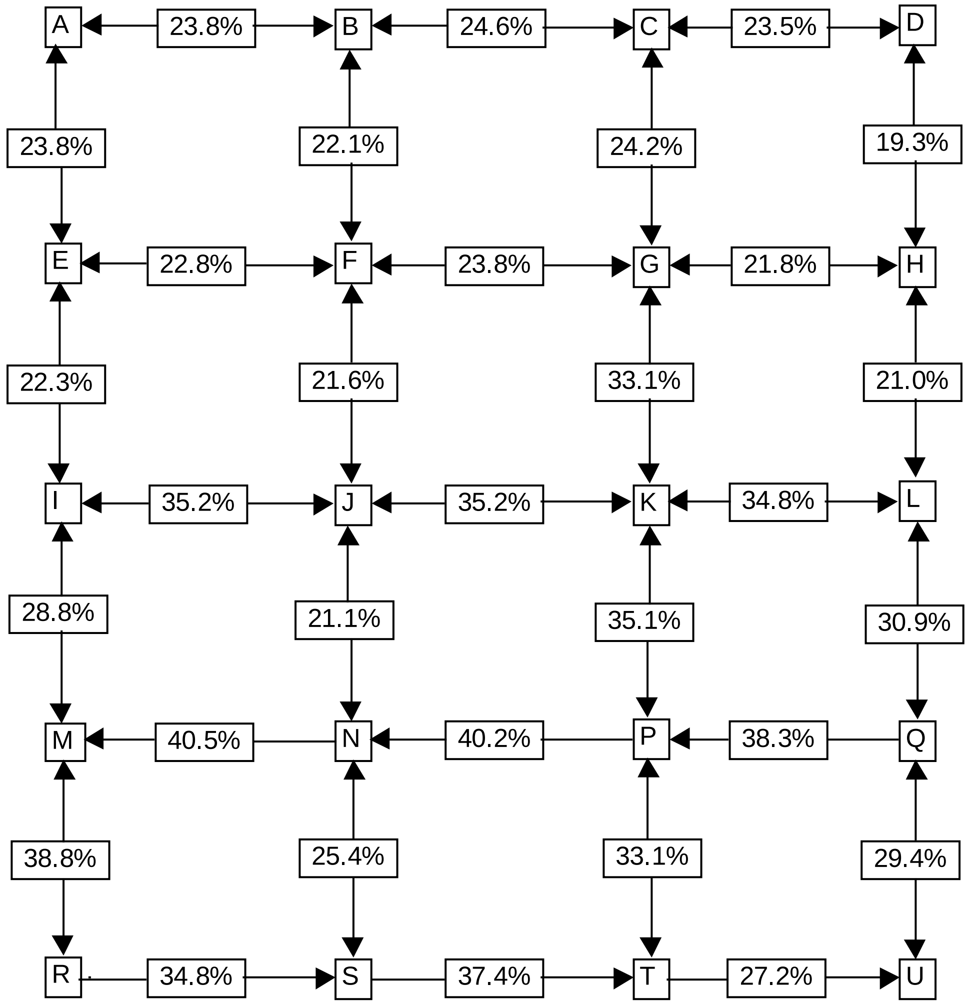


Figure 3-2. Model Performance (R^2) by Individual Detector Location (V/C = 0.5)

3.3 Flow Influence on Model Performance

Each individually detected link is associated with a simulated flow from the Monte Carlo Modeling. This simulated flow is the only internal network constraint input provided to the TMERT modeling. By plotting the detected link flow against the TMERT modeling results (R^2), the influence of flow on model performance is evaluated. However, this only isolates flow from location if the single locations are compared independently across the V/C range. Each link therefore provides 70 data points (10 runs per V/C * 7 V/C rates), which are analyzed independent of location effect. Figure 3-3 shows a typical plot for a single link with varying flow profiles. Appendix C includes the plots for each of the 31 detection locations. With the general trends of each 70-point data plot for the 31 detector locations, some inference on how flow effects model performance can be reached. The testing allows each link to be compared with other links as to whether the same general trends exist with flow effects on modeling performance.

By combining all the 31 links, with 10 runs for the 7 V/C ranges, 2,170 data points of flow by model performance are available. If those are plotted, an overall trend can be identified as a cursory look into the relationship between detected flow level and model performance. Figure 3-4 shows the plot of detected individual link flow and model performance. With only a 24%

correlation, the scatter in Figure 3-4 implies a possible secondary factor that is also influencing model performance. This is hypothesized to be a location effect based on the detector location relative to the network cordon. This is discussed in more detail later. Figure 3-5 further separates the flows by V/C range. The results of the segregation further supports another factor influencing model performance. All V/C ranges indicate that by relating flow to model performance alone produces a correlation of less than 13 percent. The regression equation for the best-fit linear line is shown on Figure 3-5, however, no correlation between increasing model performance or even the slope or intercept of the regression lines for each V/C is recognized. While regression equations may include linear, logarithmic, inverse, linear-logarithmic, and logarithmic-linear, testing of the different methods found linear regression to be the most representative.

While the correlation by V/C is poor, general trends are evident. As the V/C increases, the model performance increases for a given detector flow, supporting a V/C influence on the flow portion of the utility function. Recall that the V/C is a measure of congestion in the network and therefore congestion effects the model performance. As the congestion of the network increases, the model performance for a given flow increases. This is likely related to capacity constraint effects that begin to factor as a secondary restriction when the network congestion increases.

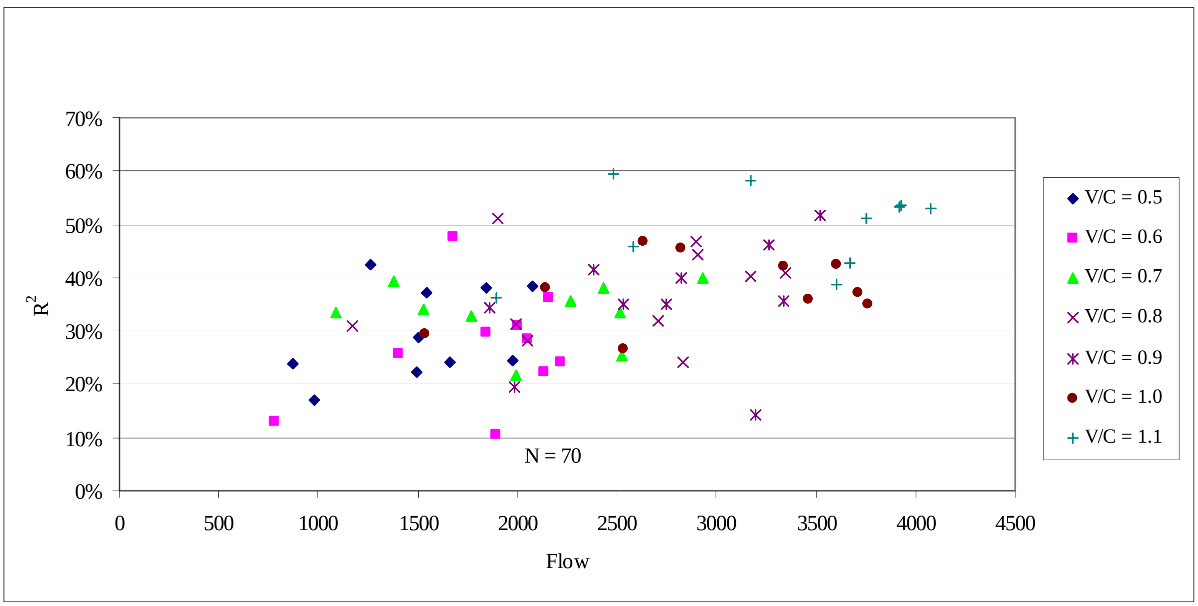


Figure 3-3. Link J-K Volume Effects on Model Performance

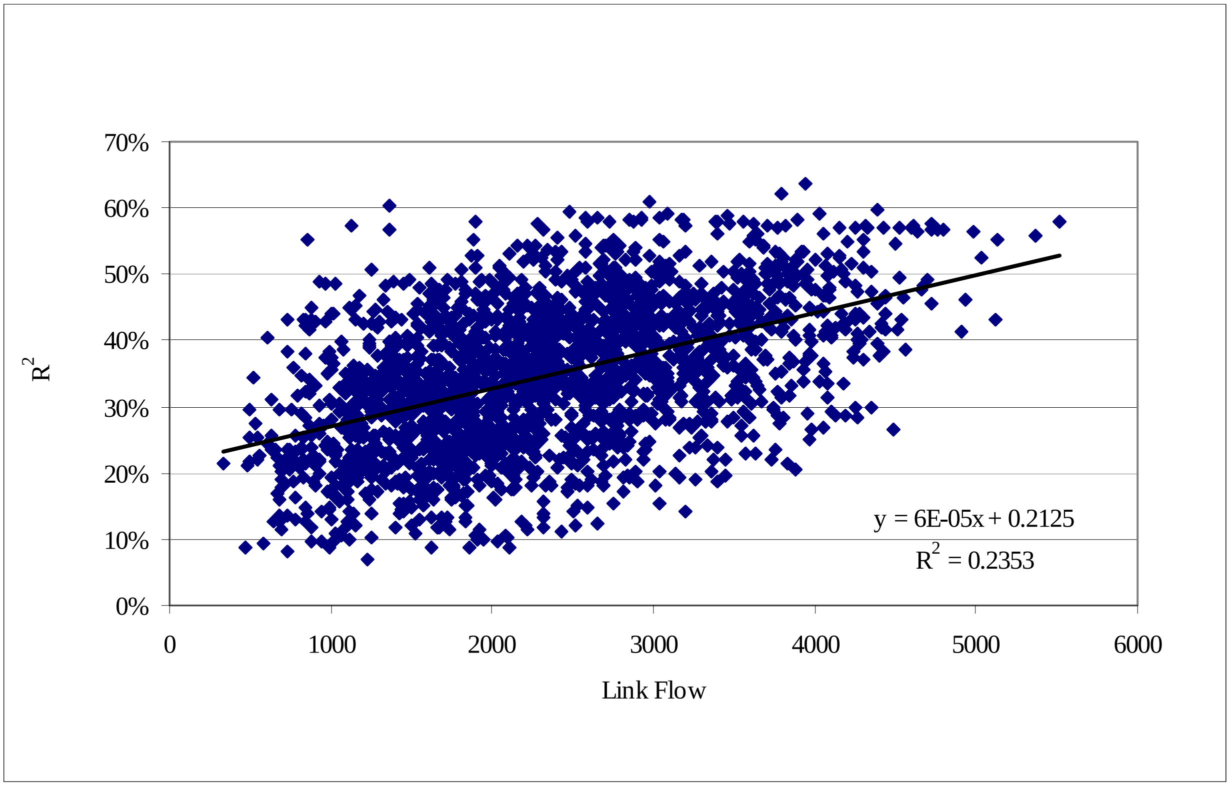


Figure 3-4. Model Performance by Flow from Individual Link Detection

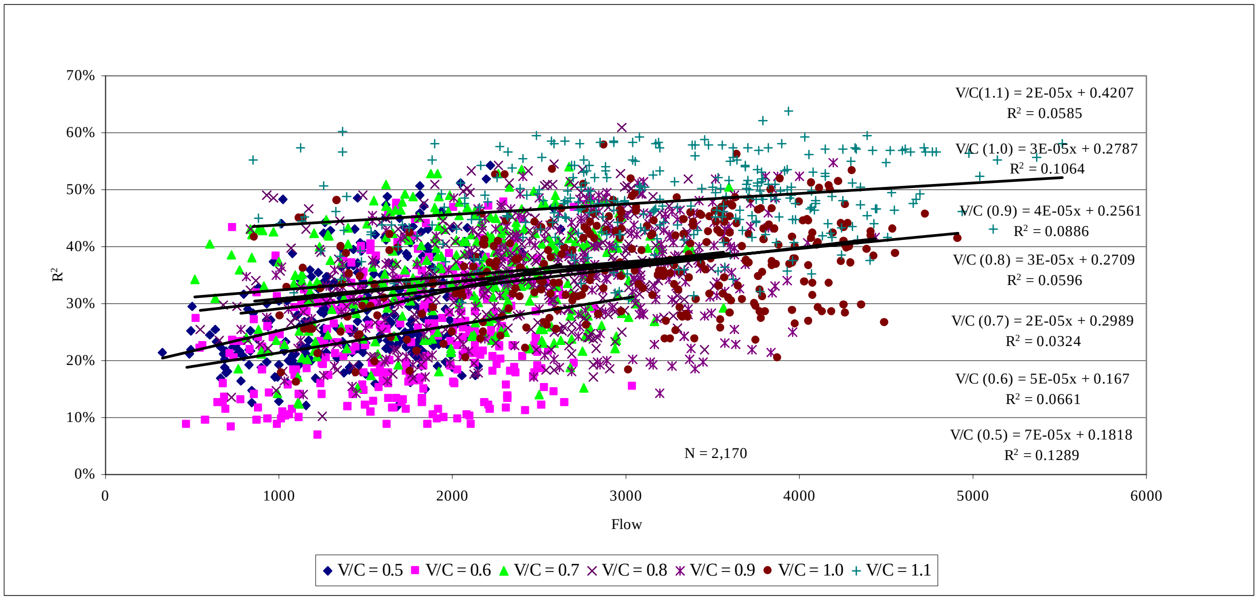


Figure 3-5. Model Performance by Flow Segregated into V/C

3.4 One-way Link Effects

Because the SLC network is comprised on both one-way and two-way links, it is questioned whether the one-way links may influence the modeling differently than the two-way links. To test this premise, the one-way links are modeled independent of the two-way flows in order to identify the potential influences. Table 3-2 compares the 6 one-way link average flows and model performance with all 31 link average flows and model performance. Each of the six one-way links were plotted in Figure 3-6 by V/C and a best-fit linear equation is developed to compare to the overall two-way link model performance. The results of Figure 3-6 support Table 3-2 in providing a general statement that there are no identifiable differences between the one-way and two-way flow's influence on model performance.

Table 3-2. Comparing One-way and Two-way link Flows and Model Performance

	Flow		R^2	
V/C Range	One-way	All	One-way	All
V/C =0.5	1,442	1,501	30%	29%
V/C=0.6	1,656	1,756	27%	25%
V/C =0.7	1,982	2,057	35%	35%
V/C=0.8	2,186	2,328	34%	35%
V/C =0.9	2,492	2,645	36%	35%
V/C=1.0	2,867	3,016	35%	37%
V/C=1.1	2,989	3,185	46%	48%

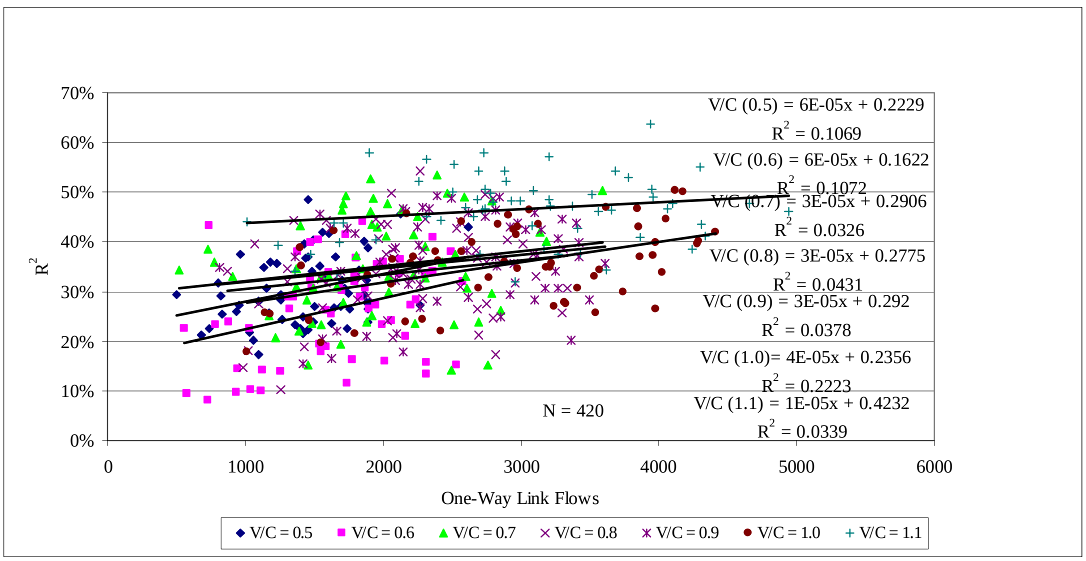


Figure 3-6. One-way Link Model Performance

3.5 Isolating Location Effects

Having identified that flow alone is not a particularly good estimator of a link's ability to estimate the model performance, another factor is hypothesized to influence determining a link's utility. This second factor is hypothesized as the location of the link within the network. Each link can be located within the network by relating its position from the cordon. Distance from the top, bottom and sides form a rating. For the SLC network, a rating of 1 to 4 is applied. This rating is a combination between the link's distance from the top/bottom and the closest side. This is measured as the number of intersections between the link and the closest adjacent cordon lines. Figure 3-7 identifies the rating for each link in the SLC network.

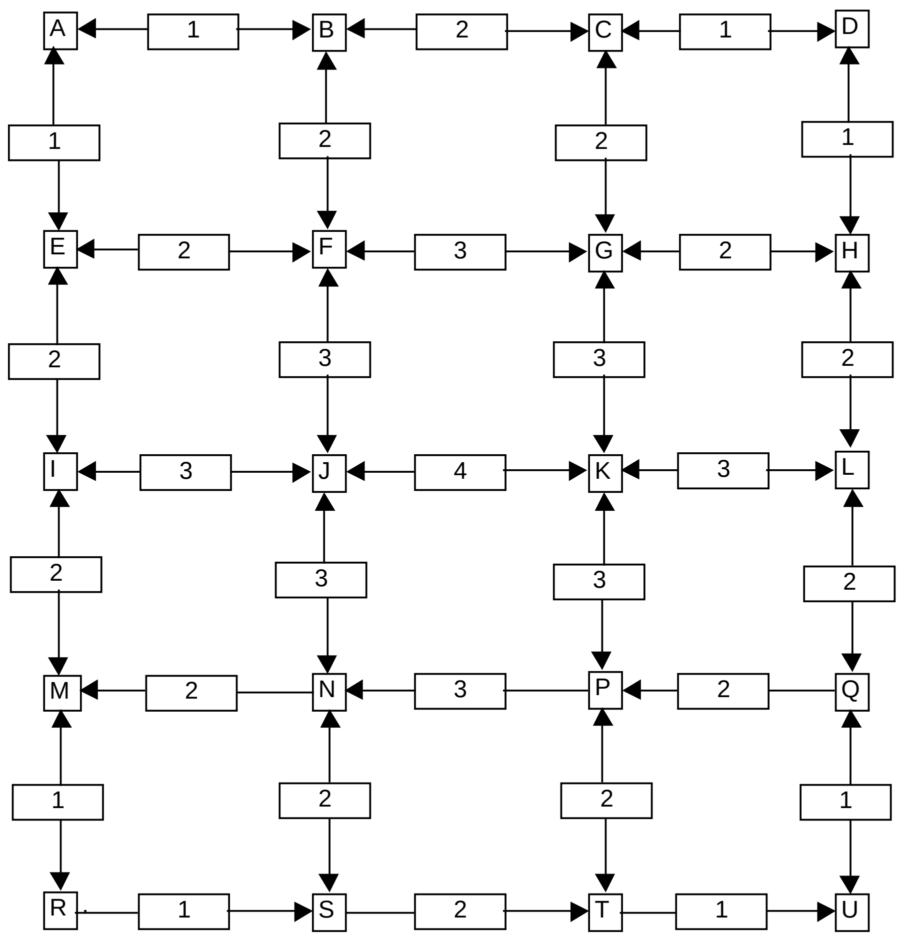


Figure 3-7. Link Location Rating

When the model performance is averaged for the individually detected links by location ratings and plotted against the model performance, the results indicate that as the location of detection progresses further from the cordon lines, the model performance improves. Figure 3-8 shows this trend for the various V/C levels. Figure 3-9 shows the data a slightly different way and allows a first impression of how both location and flow effect model performance.

Both figures indicate that model performance increases as location rating increases without exception. Similarly, the model performance increases as the V/C level increases. There are some exceptions to this general V/C trend. The lowest model performance occurs at V/C of 0.6

instead of the lowest V/C level of 0.5. This may be attributed to the lower V/C ranges which are not as limited by capacity as the higher V/C ranges and therefore more flexibility exists in the model. The only other anomaly is the location 4 of V/C level 0.8 that provides a higher model performance than V/C 0.9. A more detailed review is possible if the actual flow is plotted against model performance for the four location ratings. Figure 3-10 shows the model performance and link flow by the four location ratings. Plotting the over 2,170 TMERT model runs by location does yield more insight than the flow plots alone.

The linear best-fit lines in Figure 3-10 show that the lines diverge as the flow increases. The divergence indicates that location importance on model performance increases as a function of flow. The equations by location on the figure indicate that model performance is more represented by the location equations as evident by the increased R^2 values for each location. It is interesting to note that as the location increases, the R^2 of the best-fit curve also increases with the exception of location 4. This may be explained in that only 1 link (J-K) in the SLC network is rated at location 4 and therefore may not represent a diversified factor.

As a final investigation to location effects on model performance, the average flow is compared to the average R^2 model results for each location rating. Table 3-3 shows that as the location increases, the average flow decreases. This is expected as not all vehicles travel to the center of the network before exiting the system. Therefore, the locations rated at 1 have higher average flows than at location 3 or 4. Table 3-3 shows this decrease in average flow as location increases, yet the average model performance increases with location. This is further support that location does effect model performance and therefore is the second factor in the utility function.

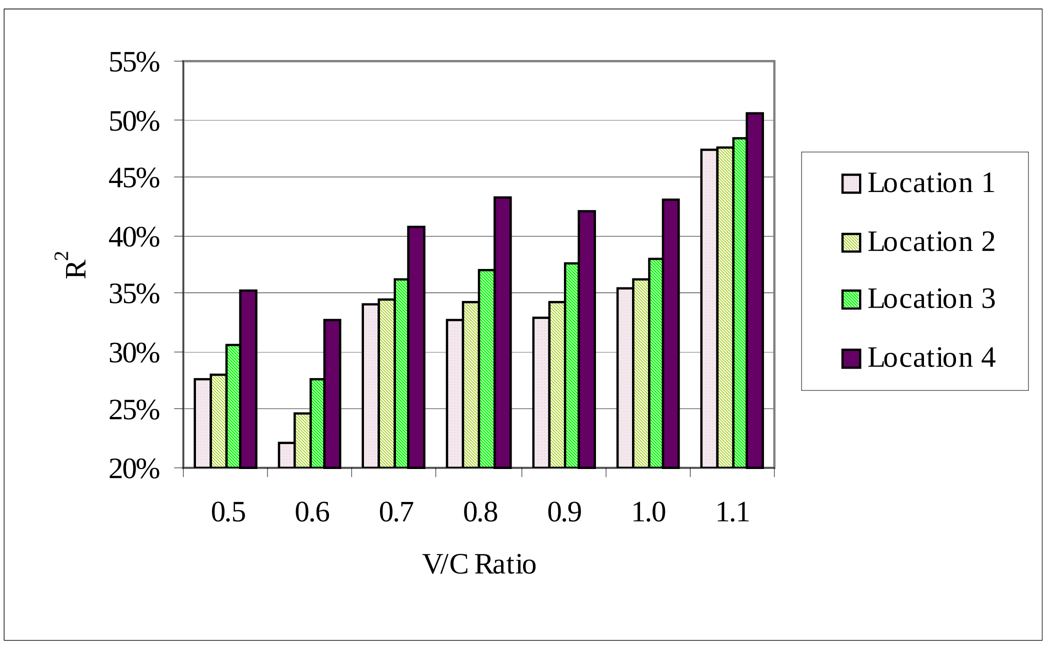


Figure 3-8. Location Factor Influence on Performance by V/C

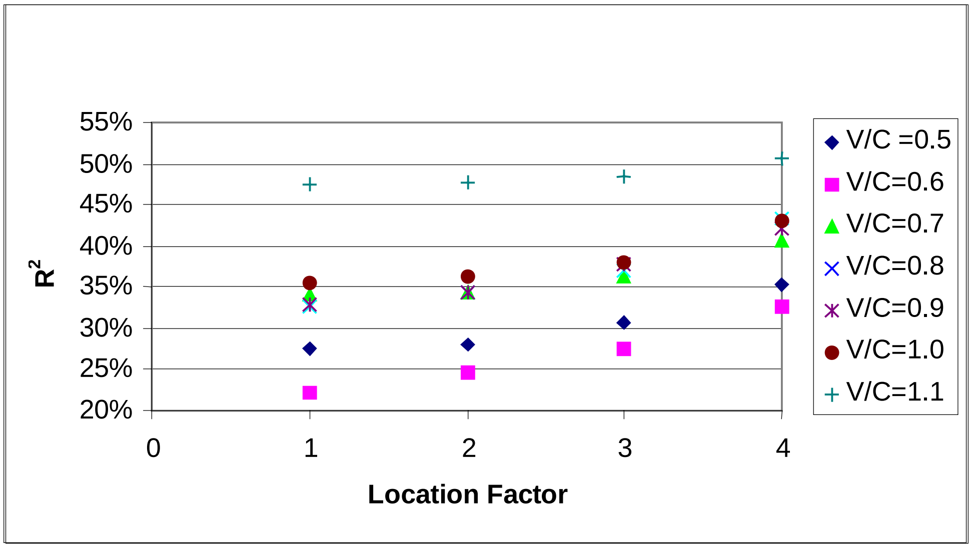


Figure 3-9. Initial Relationship between Location Factor and Increased Flow

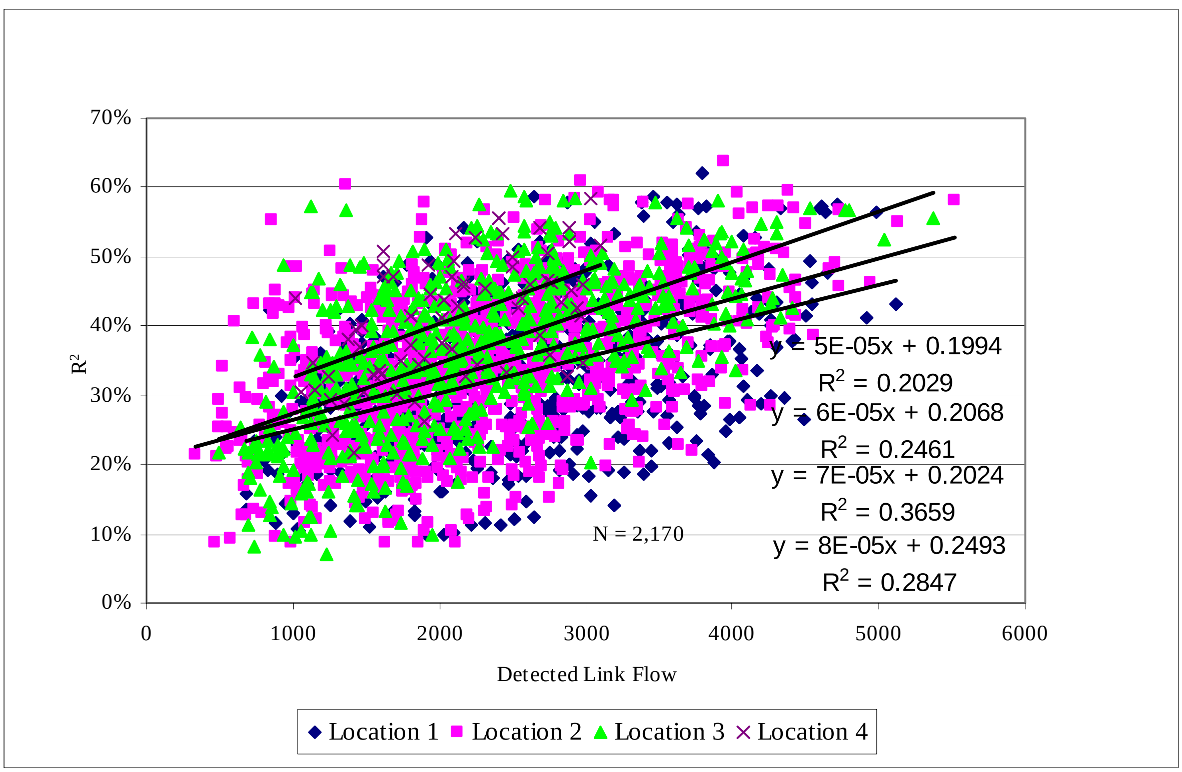


Figure 3-10. Model Performance by Link Flow as a Function of Location Factor

Table 3-3. Average Link Flow and Model Performance by Location Rating

Location	Average Flow	Average R^2
1	2,537	33%
2	2,335	34%
3	2,242	37%
4	2,093	41%

3.6 Increasing Network Detection by Volume

Once the preliminary relationships are developed between location and flows for individual link detection, consideration is given to multiple detector coverage sites. The addition of detectors can be based on flow or some logic influenced by location. When basing the location on flow, the highest flow link is selected for the initial detector location. The subsequent detectors are added in a descending order from highest flows to lowest flows. This is referred to as High-to-Low detection. Building from 1 to 31 detected links and for the 10 independent simulation runs provides 310 TMERT runs for each V/C ratio. Figure 3-11 shows the plot of model performance as a function of detection coverage for the 7 V/C ranges. Individual V/C plots are available in Appendix D. Each V/C plot of increasing detection provides a regression equation based on 310 data points. The opposite method of detecting from Low-to-High flow level is also investigated. Figure 3-12 identifies the plot of model performance as a function of detection coverage for the 7 V/C ranges. Individual plots are available in Appendix E.
The difference between the High-to-Low and Low-to-High indicates that model performance improves faster when detector coverage is increased based on High-to-Low than from Low-to-High. The High-to-Low is best represented by a natural log regression curve while the Low-to-High is best represented by a linear regression. Equations for the High-to-Low and Low-to-High regression curves and associated R^2 are shown in Table 3-4 and 3-5 respectively.

For any given model performance requirement, more detectors are required of the Low-to-High placement strategy than the High-to-Low. For example, if a minimal model performance of 80% is required, then the High-to-Low method requires 30% detector coverage while the Low-to-High requires 75% to 80% detector coverage. From Figure 3-11 the improvement by coverage is similar for each V/C range and is well correlated with an average R^2 above 90%.

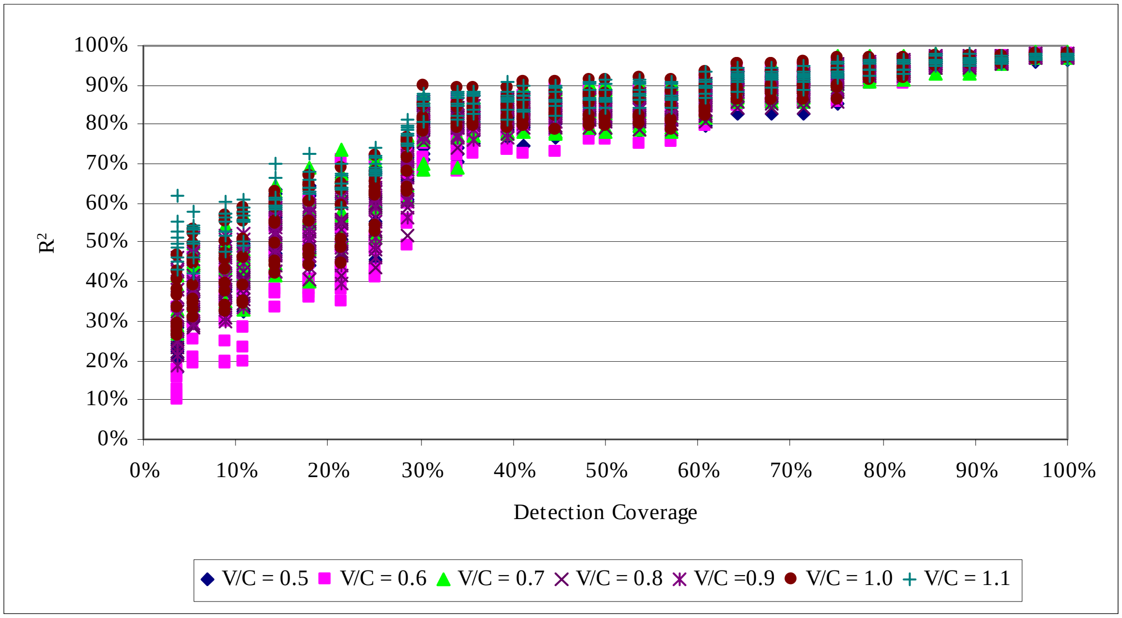


Figure 3-11. Increasing Detector Coverage from High-to-Low for all V/C

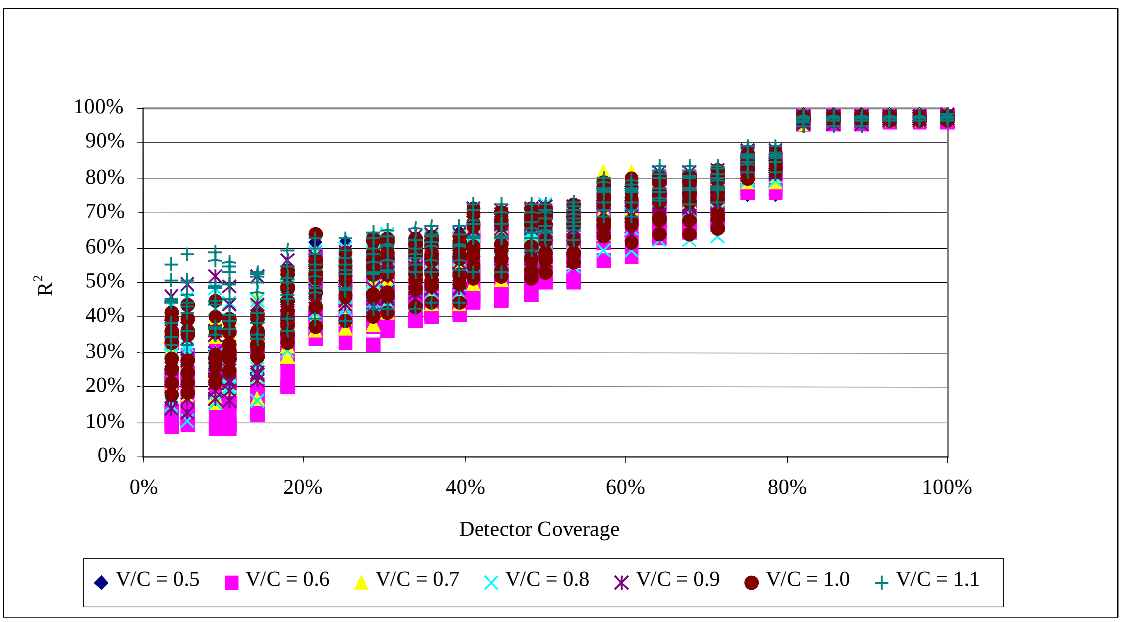


Figure 3-12. Increasing Detector Coverage from Low-to-High for all V/C

Table 3-4. High-to-Low Regression Equations by V/C

V/C	Regression Equation	R^2
0.5	y = 0.2299Ln(x) + 0.984	94%
0.6	y = 0.2583Ln(x) + 0.994	89%
0.7	y = 0.211Ln(x) + 0.9883	90%
0.8	y = 0.2319Ln(x) + 0.9844	91%
0.9	y = 0.2195Ln(x) + 0.9875	91%
1.0	y = 0.2096Ln(x) + 0.9896	90%
1.1	y = 0.1671Ln(x) + 0.9851	92%

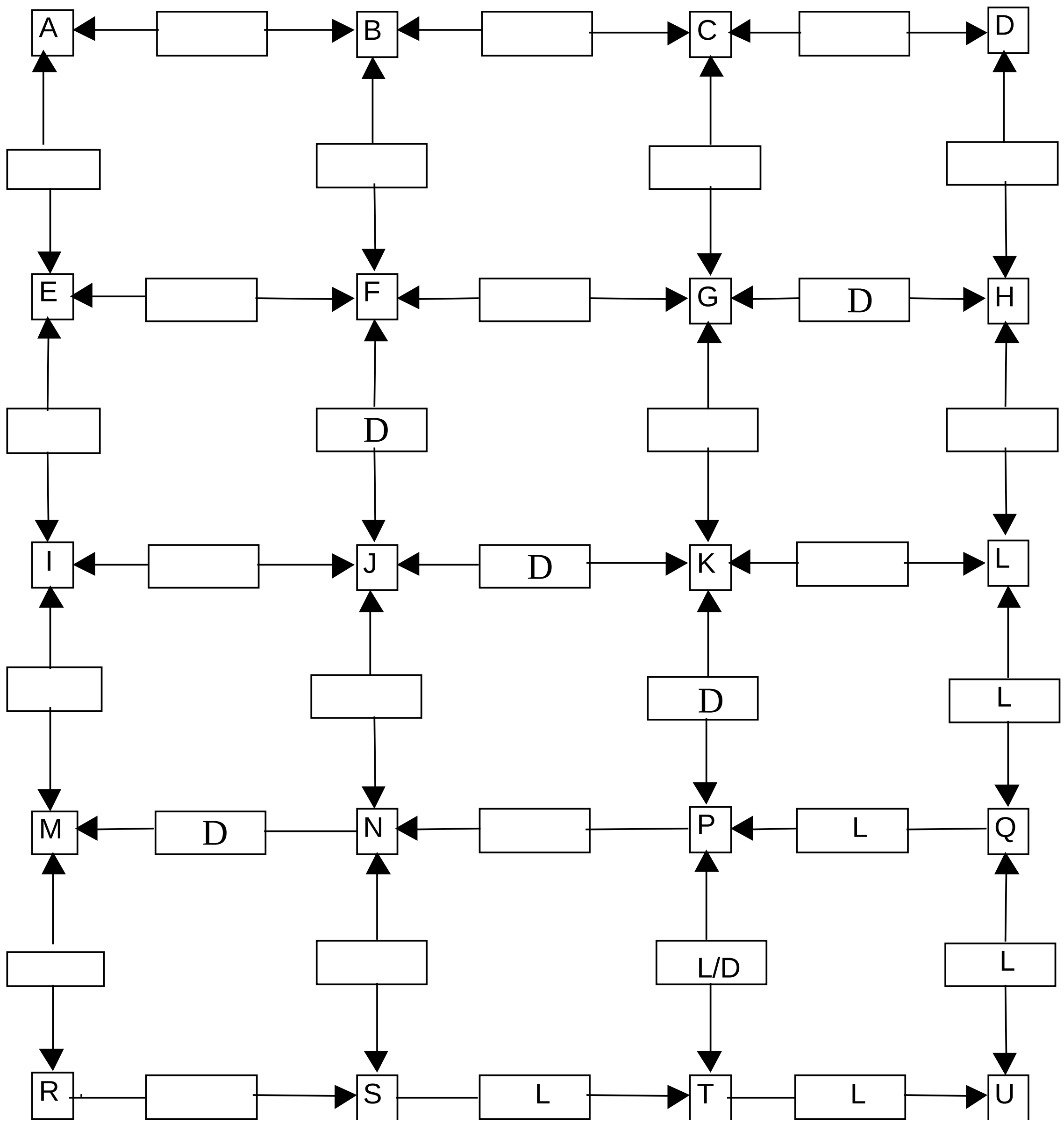
Table 3-5. Low-to-High Regression Equations by V/C

V/C	Regression Equation	R^2
0.5	y = 0.8348x + 0.1918	94%
0.6	y = 0.8871x + 0.1421	93%
0.7	y = 0.77x + 0.2543	93%
0.8	y = 0.7555x + 0.2639	91%
0.9	y = 0.7566x + 0.2718	91%
1.0	y = 0.737x + 0.285	92%
1.1	y = 0.6239x + 0.3812	91%

3.7 Comparing Distributed Network Detection with Localized Detection

The results of the individual link enumeration indicate that location has an impact on model performance. To test this, the network is assigned 6 detectors under two location patterns. The first pattern bases the detection on an evenly spaced logic. The second pattern utilizes highly concentrated detection in one section of the network. Figure 3-13 shows the links detected for the Localized and Distributed detector patterns. The 10 runs from V/C 0.8 are incorporated into the analysis.

To minimize the impacts from flow, the net sum of each detection pattern is based on similar flow level. This implies that all links detected sum to a similar total detected flow level within 5% for both location patterns. The results of the 10 runs at V/C 0.8 are shown in Table 3-6 indicating that the distributed pattern provides an average 17% better overall model performance than the concentrated localized detection pattern.



L = Localized Detector Location D = Distributed Detector Location

Figure 3-13. Detector Pattern for Localized and Distributed Pattern

Table 3-6. Comparing Distributed and Localized Detection Patterns

V/C 0.8	Distributed	Localized	D>L
Run 0	56.5%	43.3%	30%
Run 1	55.9%	42.9%	30%
Run 2	55.1%	48.6%	13%
Run 3	61.3%	52.8%	16%
Run 4	56.9%	49.7%	14%
Run 5	66.1%	61.4%	8%
Run 6	63.5%	49.9%	27%
Run 7	62.8%	57.9%	8%
Run 8	59.3%	57.2%	4%
Run 9	63.2%	54.4%	16%
Average			17%

D>L = The percentage that the Distributed R^2 is greater than Localized R^2 modeling results

3.8 Location Detection Comparison

A second stage in the location testing is to detect a similar number of each location type and compare the model's performance with the same location ratings detected. For the SLC network, there are 8 links of location 1, 14 links of location 2, 8 links of location 3 and 1 link of location 4. Because there are 8 location 1 and 8 location 3 links, these were selected for the comparison. Figure 3-13 identifies the locations of the two location patterns. Figure 3-13 indicates that location 1's are along the network edge. Location 3's are more centralized providing insight into the network interior. As the discussion in Section 2 stated, this is similar to a jigsaw puzzle in that the interior detection should provide more insight because it reduces the distance between unknown network flow elements and allows the estimates to be based on data less remote.

Table 3-7 provides the results for the Location 1 and Location 3 detection patterns showing that the Location 3 detection does provide an improved model performance over the Location 1 detection pattern. This example provides support on the network location effects in determining detector location. The localized and distributed network pattern incorporated similar flows on the detected links of the two detection patterns in order to reduce the effects of traffic flow. However, the detection based on location rating does not allow the links to be selected and therefore there is a disparity in detection volumes. Table 3-7 includes the sum of link flows for each location pattern for the 10 runs of V/C 0.8. The sum of Location 1 links is higher than Location 3 links and therefore is a concern that the effects of location may be reduced because of the higher flows on Location 1 links.

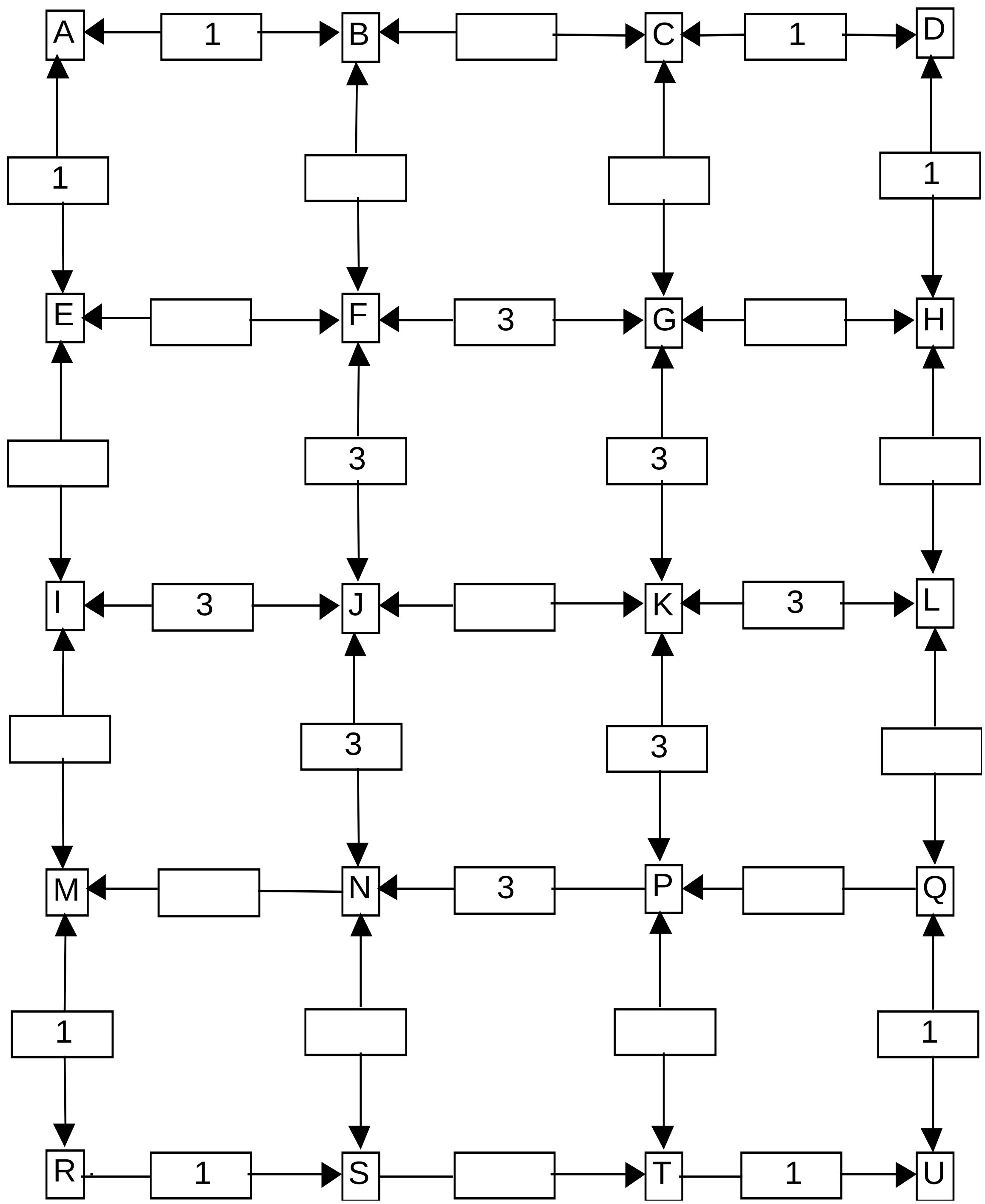


Figure 3-14. Detector Pattern for Location 1 and Location 3 Pattern

Table 3-7. Comparing Location 1 and Location 3 Detection Patterns

V/C 0.8	Location 1		Location 3		% 3 / 1	% 3 / 1
Run	Link Flows	R^2	Link Flows	R^2	Flow	R^2
Run 0	20,435	55.7%	15,645	62.6%	77%	112%
Run 1	21,223	50.3%	19,048	59.8%	90%	119%
Run 2	20,482	58.1%	17,636	62.2%	86%	107%
Run 3	20,162	63.2%	18,009	68.0%	89%	108%
Run 4	19,594	53.1%	16,714	61.9%	85%	117%
Run 5	22,210	60.0%	16,735	64.9%	75%	108%
Run 6	17,180	54.0%	15,903	70.4%	93%	130%
Run 7	18,423	44.4%	18,845	71.0%	102%	160%
Run 8	22,572	58.8%	17,843	64.1%	79%	109%
Run 9	19,291	37.7%	18,803	68.5%	97%	182%
Average					87%	125%

% 3 / 1 is the percentage of Location 3 value over Location 1 value

It is expected that Location 1 links will have higher flows than Location 3 since Location 1's are on the outside of the network near the entering and exiting cordon loads. Location 3 is internal to the network and not all vehicles pass through the center of the network, therefore potentially reducing average internal flows. Since it is identified that higher flows produce higher model performance, the higher flows for Location 1 would support larger R^2 than Location 3 if location were not a factor. Table 3-7 indicates the contrary. While the flows for Location 1 are larger, the model performance is poorer. On average for the 10 runs, the Location 3 link flows are only 87% the Location 1 flows, yet the average Location 3 R^2 is 25% greater than Location 1 R^2.

3.9 Model Error as Flow Approaches Capacity

While the purpose of this research is not evaluating the TMERT model performance, one issue is investigated that directly relates to the TMERT model. The error being produced by the model is measured as flow along the error arcs. Since congestion traffic levels are one of the areas being investigated by the detector location-allocation research, it is interesting to identify how the model performance degrades with congestion. In comparing the model, similar detection patterns must be compared to minimize external factors on the modeling results. While increasing the network detection from a single link to saturation coverage, each representative detector coverage level can only be compared if the same link detection occurs for each V/C. Saturation coverage provides the most potential for error as each link is detected and thereby maximizes the error arcs located on the network. By comparing the 7 V/C ranges with 10 runs per V/C range provides 70 data points.

No pattern with the error arc flows and V/C is identified and it is interesting to note that the error arc flow for each TMERT run never exceeded 13 vehicles, less than .05% of the network flow. This is important to establish that the differences in model performance are related to the flow and location inputs and not simply variability in the model performance. If it were determined that as flow increased, the model's error significantly increased, then the results would be questionable due to inherent model variability.

3.10 Analysis Summary

The individual detection of each link within the network provided insight as to how the flow and location effects modeling results. It was anticipated that utilizing flow inputs, with higher flow volumes, would provide an increase in model performance. However, preliminary results provided a wide scatter for a given V/C ratio. It was found that all links could not be plotted on the same graph due to the impacts of location as the link detector moved throughout the model. When the analysis was readjusted to only compare one location at a time and compare across V/C ratio, it was found that the correlation increased and the anticipated results are supported. Increasing network detection is then discussed by increasing internal detection based on link flow level. Detection is first examined for increasing based on providing detection on the highest flow links and then systematically increasing based on the next highest flow. The reverse is also explored by increasing from lowest flow to highest flow. The results indicate that flow does play a critical role in modeling. When location decisions are based on the High-to-Low policy, a given model result level is reached with reduced detector coverage than when locating based on the Low-to-High policy.

Multiple detector patterns are tested through two methods. The first method compares dispersed detectors throughout the network with concentrated detectors in one location. Six detectors for each pattern with the sum of detected links similar in total detected flow showed that a dispersed pattern provides a better model performance than the concentrated location pattern. The second method compares detection based on network Location rating. The results show that even with less flow on the links, a centralized location pattern provides superior model performance to a higher flow exterior location pattern.

Having explored the impacts of flow and location on model performance, the next section develops the results and expands the analysis to developing the Utility Equation described in Section 2 in order to quantify the impacts of each factor. The two components, location and flow, are compared to produce the final calibrated Utility Equation for rating each links detection value in a network.

4.0 INCORPORATING ANALYSIS INTO UTILITY RELATIONSHIP

The enumeration analysis in this section shed insight onto how both flow and location effect the model performance. While general trends are obvious, none of the analysis provided sufficient correlation to provide a reliable method for determining exactly how the model performance improves as a function of both flow and location. However, this information may still be useful if it is compiled into the Utility Equation. The shortfalls in the analysis results imply that the Utility Equation should be applied as a general guide instead of a 100% accurate methodology. Section 4 discusses how each component, flow and location, are compiled into the Utility Equation. Calibration of the Utility Equation develops the relative importance of each component on the overall Utility rating for each link within the network.

4.1 Flow Level

Figure 3-4 is the first insight into the relationship between flow and model performance. The best-fit curve indicates that the model performance increases by 6% per 1,000 increase in vehicle flow. While the correlation of the regression curve from the individual link analysis may be characterized as poor, there is precedence in transportation application where regression curves with lower R^2 are utilized. The ITE Trip Generation Manual (ITE, 1997) provides vehicle trip rates for various land uses and requires an R^2 of only 25% before the regression equations can be applied.

When the data is segregated by V/C as in Figure 3-5, the results are regression lines where the model performance increases with increased V/C for the same flow levels. This supports an idea that not only is the volume of flow improving model performance, the level of congestion provides additional impact, most likely due to upper bound constraints which begin to limit flow conditions.

The linear regression curves from the V/C segregated data are shown in Table 4-1. If these regression equations are applied to five flow regimes as identified in Table 4-2, and plotted in Figure 4-1, they form representative relationships between flow, V/C and model performance.

Table 4-1. Linear Regression Equations for V/C Segregation

V/C	Regression Equation
0.5	y = 0.07x+0.18
0.6	y = 0.05x+0.17
0.7	y = 0.02x+0.13
0.8	y = 0.03x+0.27
0.9	y = 0.04x+0.25
1.0	y = 0.03x+0.28
1.1	y = 0.02x+0.42

y is projected model performance, x is in 1,000 of vehicles

Table 4-2. Model Projections Using Linear Regression by V/C Range

			Flow (in 1000)			
V/C	0	1	2	3	4	Difference
0.5	18%	25%	32%	39%	46%	7%
0.6	17%	22%	27%	32%	37%	5%
0.7	30%	32%	34%	36%	38%	2%
0.8	27%	30%	33%	36%	39%	3%
0.9	25%	29%	33%	37%	41%	4%
1.0	28%	31%	34%	37%	40%	3%
1.1	42%	44%	46%	48%	50%	2%

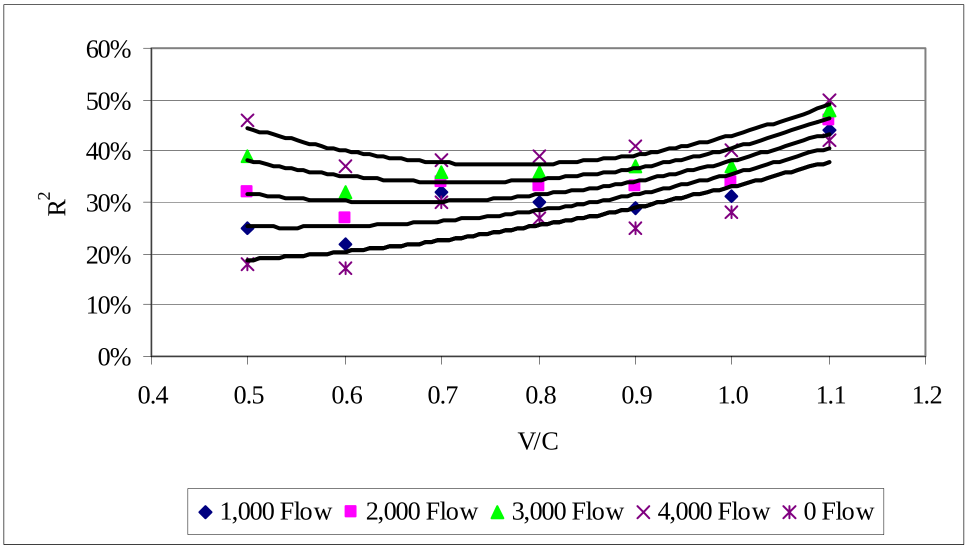


Figure 4-1. Regression Analysis of Segregated V/C Ratio and Flow Profile

Table 4-2 shows that at a given V/C range, the change between each equal flow regime is constant. This is expected due to the linear regression equation being applied. Figure 4-1 plots the V/C ranges for the five flow profiles and shows a second set of regression curves that are best represented by a second order polynomial.

To summarize, the initial set of regression equations, from Figure 3-5 and shown in Table 4-1, indicates that the relationship between flow and V/C range is better represented by a second order polynomial as described in Table 4-3.

The shape of the second order regression equation is related to the V/C ratio. The differences between the constants are a function of the flow profile and can be incorporated into general factors. From Table 4-3, constant changes occur in the factors between flow profiles. A general equation is developed using an estimate of model performance defined as a function of V/C ratio and link flow. The new general equation represents a measure of identifying the impacts of flow and V/C on the model performance.

$$y = [0.32 + 0.18x]z^2 – [0.2 + 0.35x]z + [0.2 + 0.2x] \qquad \text{Eq. 4-1}$$

Where:

y is an estimated model measure

x is flow in 1,000's

z is V/C ratio from 0.5 to 1.1

Table 4-3. Flow Specific Regression Equations Based on V/C Ratio

Flow Profile (in 1,000s)	Regression Equation	R^2
0	$y = 0.3214z^2 - 0.1964z + 0.2057$	70%
1	$y = 0.5z^2 - 0.5429z + 0.3986$	71%
2	$y = 0.6786z^2 - 0.8893z + 0.5914$	74%
3	$y = 0.8571z^2 - 1.2357z + 0.7843$	77%
4	$y = 1.0357z^2 - 1.5821z + 0.9771$	79%

y = model performance, z is V/C ratio

4.2 Location

If a similar analysis for location is evaluated, then Figure 3-10 provides the initial regression analysis by location. The linear regression equations allow the data to be divided into a location element that is then compared by flow profile as in Section 4.1. Table 4-4 shows the initial linear regression equations from Figure 3-10. The linear regression calculates the estimated model performance for four flow profiles shown in Table 4-5.

The divergence of the linear slopes as the location rating increases, indicates that the location rating importance increases as the flow profile increases. This is illustrated in Table 4-5 by the change between location 1 and location 4 for each flow profile. At flow profile 1, the change between Location 1 and Location 4 is 11%. As the flow profile is increased the change between Location 1 and Location 4 increases by 3%. Table 4-5 supports the conclusion that as flow increases, a uniform increase in model performance is expected for a given location rating. The uniform increase becomes greater with increased location rating. The change between location rating of a given flow profile increases as the flow profile increases. These statements are illustrated in Figure 4-2 with the regression equations being exponential and described in Table 4-6. By combining the equation, similar to Section 4.1, a general single equation represents the estimated model performance as a function of location and flow. The exponential regression equations are comprised of the constant, C, and the power, D as shown in equation 4-2.

The constant C is represented as a function of flow in Equation 4-3. The power D is represented by a function with respect to location as shown in Equation 4-4. The final result is a single general equation (Utility Equation) that estimates model performance as a function of flow and location rating. This general relationship provides a mechanism for identifying each potential detector location's value. Note that the form of the Utility Equation has changed from the hypothesized Equation 2-3.

$$y_i = Ce^{DL_i} \qquad \text{Eq. 4-2}$$

with

$$C = 0.18 + 0.04x_i \qquad \text{Eq. 4-3}$$

$$D = 0.112 * 1.05(L_i - 1) \qquad \text{Eq. 4-4}$$

where:

y is model estimate for link i

x is flow in 1,000s on link i

L is Location Rating for link i

Table 4-4. Linear Regression Equations Based on Location

Location Rating	Linear Regression Equation
1	$y = 0.05x + 0.20$
2	$y = 0.06x + 0.21$
3	$y = 0.07x + 0.20$
4	$y = 0.08x + 0.28$

y = model performance, x is flow in 1,000s

Table 4-5. Model Projections Using Linear Regression by Location Rating

	Flow Profile (in 1000's)				
Location Rating	1	2	3	4	Δ between Flow Profiles
1	25%	30%	35%	40%	5%
2	27%	33%	39%	45%	6%
3	27%	34%	41%	48%	7%
4	36%	44%	52%	60%	8%
Δ between Location 1 and 4	11%	14%	17%	20%	

Table 4-6. Exponential Regression Equations for Location Effects

Flow Profile	Exponential Regression Equation	R^2
1	$y = 0.2165e^{0.1094x}$	77%
2	$y = 0.2598e^{0.1179x}$	86%
3	$y = 0.3031e^{0.1238x}$	91%
4	$y = 0.3464e^{0.1281x}$	94%

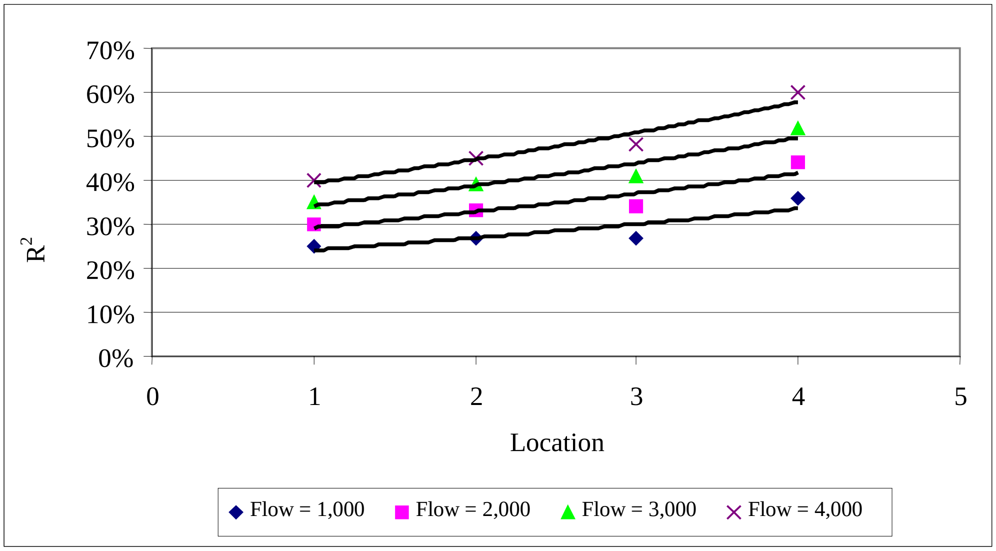


Figure 4-2. Location Impacts as a Function of Flow Profile

To test the validity of the developed Utility relationship, a comparison of the 4 location ratings and 4 flow profiles (16 combinations) is executed between the Utility Equation and the results of the location linear regression of Tables 4-4 and 4-5. Table 4-7 shows the results of this comparison and Figure 4-3 plots the data showing an R^2 of 95%.

Table 4-7. Comparison of Utility and Linear Regression

Flow Profile (in 1,000s)	Location Rating (L)	Exponential Equation	Linear Regression
1	1	25%	25%
1	2	28%	27%
1	3	32%	27%
1	4	37%	36%
2	1	29%	30%
2	2	33%	33%
2	3	38%	34%
2	4	44%	44%
3	1	34%	35%
3	2	38%	39%
3	3	43%	41%
3	4	50%	52%
4	1	38%	40%
4	2	43%	45%
4	3	49%	48%
4	4	57%	60%

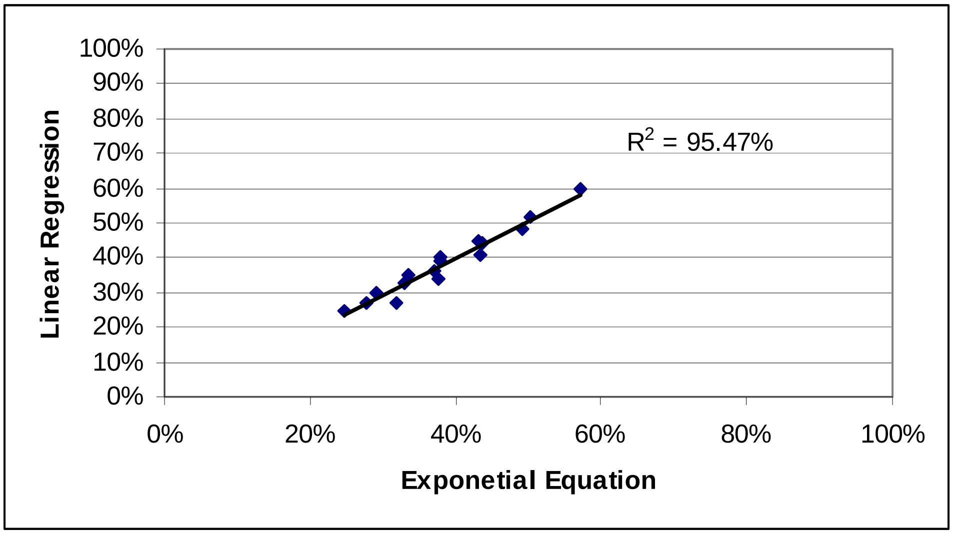


Figure 4-3. Comparison of Utility and Linear Regression

4.3 Testing Utility Performance

It is expected that the Utility Equation will compare well with the linear regression because it is developed from that data. Recall that the location factor linear regression only produced R^2 values of 20% to 37%. Therefore, the Utility Equation is based on a linear regression model that is not highly accurate. This provides the Utility Equation as only valuable as a preliminary indicator of potential locations. To test the capabilities of the Utility Equation (Eq. 4-2), it is compared to the individual link enumeration process. By calculating the Utility Equation value for each link in the network and comparing the TMERT modeled and Utility Equation rankings, the capability of the Utility Equation can be ascertained. Note that the R^2 values will not and do not need to be identical for each method. The measure of the Utility Equation's capability is how well it ranks the potential detector locations compared to the ranking through the enumeration process.

The 10 runs of V/C 0.8 are applied in the comparison analysis. The results are provided in Table 4-8 showing the Utility Equation to provide on average a ranking within 3 of the enumeration ranking. While 26 of the 31 links were within the 3 ranking places of one another, the remaining 5 ranged from 4 to 10 places from the enumeration ranking. This limitation characterizes the Utility Equation as a general guide.

Table 4-8. Rating Differences Between Utility Equation and Enumeration Process

Rating Difference (RD)	Average Compliance 10 Runs (V/C = 0.8)
0	3
1	12
2	7
3	4

>3	5
Average RD	3

RD = Rating Difference is the difference between the ranking from the Enumeration Process and the Utility Equation

4.4 Utility Equation Summary

Relationships between model performance as a function of flow and V/C, and model performance based on flow and location rating are both provided in general form to allow calculations without implementing the TMERT model. This estimated model performance is a method for determining the likely value of each potential detector location within the network. This ranking is then available for allocating detection units to provide the most value for a user's investment.

From the enumeration process, the linear regression equations are combined and manipulated to determine a general Utility Equation that incorporates the effects of both flow and location. This Utility Equation is then capable of ranking the potential detector locations and identifying the best method for allocating resources. However, care must be taken as the Utility Equation only provides a general guide. Further refinement is likely necessary before it can be confidently applied.

5.0 CONCLUSIONS

The research presented supports the development of a Utility Function to provide a method of rating each link within a network for its value in locating a vehicle detection device.

The investigation methodology incorporated an on-line traffic model that infers both turning movements and link vehicle flows from detected flows in a small recurring interval that qualifies the model for real-time applications. The TMERT model as it is known has a controlling algorithm borrowed from the field of Operational Research where it has been successfully implemented in use of electrical and water distribution networks.

As identified in the research proposal, the investigation evaluates model performance as related to the parameters of network congestion, percentage of the links arcs with detector coverage, flow on the links, and the location of the detectors. A Monte Carlo model is developed based on observations from a 20-intersection network in downtown Salt Lake City, Utah. The observations included turning movements, cordon flows, and internal link flows.

It was hypothesized that as detection coverage increased, the model performance would increase with diminishing returns whereby additional detectors did not improve the modeling results. Further it was posed that the influence of a single detector on modeling performance is related to flow on the link and the link's relative position within the network. An enumeration process of individual link detection and multiple detection patterns is implemented to validate and test the theory. These objectives are fulfilled from the analyses presented which are summarized by the following supporting conclusions:

- A developed Utility Equation is a function of flow and location, providing a general guide for Transportation Engineers to evaluate the importance of each link within a network.

- If only link flows are considered, the placement of detector should be based in a descending order from highest to lowest flow in order to maximize the improvement to model performance.

- For a given flow level on links, a distributed detector layout pattern provides improved model performance when compared to a localized pattern.

- Internal network detection produces superior model performance over peripheral detection, even when the peripheral link flows are higher.

5.1 Future Work

As with most research, in searching for the answers to one question, more questions are raised. This research stands alone as providing insight into the need for optimal use of vehicle detection. The following directions of work are recommended to further the science of traffic detection location and allocation in optimizing available resources.

1 Test the methodology on other networks to ensure the conclusions are substantiated on various network configurations.

2 Work with local agencies (UDOT, Wasatch Front Regional, and Salt Lake City) to improve the haphazard methods they employ. Discussions have already begun with UDOT and Wasatch Front Regional Council who are interested in enhancing their methodology to provide a foundation with scientific rigor.

3 Consider the interaction of internal detectors to evaluate how the placement of one internal detector, influences the ranking methodology for the subsequent detector locations. The Utility Function may be better represented by a dynamic response whereby the importance of subsequent detection location is related to the existing internal detectors. This is proposed in Equation 2-4 and the subsequent discussion.

4 Evaluate how using video detection to detect entire intersections, link approach and departure volumes as well as turning movements, may improve the ability of the TMERT model.

5 Incorporate a detector reliability element in determining the optimal detector layout and coverage pattern. When detectors fail, an overlap in coverage should be included so that sufficient detection remains for adequate model performance.

While the research presented has attempted to minimize the variables by not modifying or improving TMERT operation, TMERT improvements are also necessary. Some of the TMERT modeling improvements that allow a more complete transportation tool include:

1. Using TMERT in Incident Detection applications. With incident detection, TMERT can identify excess capacity for developing re-routing strategies.

2. Using TMERT as a Planning Tool to evaluate the impacts to traffic of land use development within the network.

3. Incorporating TMERT with GIS into a GIS-T application improves the interface and allows for easier accessibility and facilitates incorporating GPS application for emergency services, transit and VIPs.

5.2 Summary of Research Accomplishments

This research provides insight into how the detection location impacts model performance. Detector locations with high flows distributed throughout the network provide the best modeling results. The Utility equation allows each link to be evaluated and an importance rating placed on the network links. When combined with the proposed future work, the ranking method may well provide a model (TMERT) that eliminates the need for saturation detection for adaptive control signal systems. Once detection requirements are reduced, the cost for installing an adaptive control signal system may be reduced to the level that widespread implementation may occur. The benefits of adaptive control are well documented, however they can only be realized when these systems are implemented and to date, cost constraints have limited their use. This research supports a method for reducing the overall costs for these systems and providing an attractive alternative to saturation detector coverage.

5.3 Research Contribution

With increasing traffic congestion and rising land and road construction costs, the emphasis of traffic engineers in urban settings has recently focused on more efficiently utilizing the existing capacity of the street network. For most forward thinking urban areas, the "old school" of accommodating demand by increasing capacity through construction is transforming into a philosophy of ensuring optimal use of existing systems before new construction is considered. To accommodate this increasing need for transportation system optimization, new areas of transportation modeling are being explored with particular emphasis on real-time, on-line systems that adapt to the detected traffic demand.
Many of the rising transportation models center on increased computer processing time to allow for these real-time transportation applications. These new applications, however, are typically developed in a research setting and employ comprehensive knowledge of the network. This implies the use of saturation coverage of traffic detectors. When one considers the cost and person resources required to completely detect an entire city network, the costs become a significant concern. While the prospect of a fully detected city is appealing, the reality is that few cities are willing to make the investment required to make this concept a reality. The research community's use of saturation coverage in model development can be directly linked to the rift between the "State-of-the-Art" and practical implementation.

Few scientifically supported methodologies exist for locating and allocating detector resources. Discussions with Federal, State, County, and City officials, as well as Foreign experts from Asia and Europe, has led to the conclusion that most approach the need for determining when and where detectors should be located in an ad hoc form. Some place detection based on specific localized need such as recurring accidents, a bottleneck or violation frequency. Others simply place detectors out of historic habit. When advanced technology is implemented, most succumb to using saturation detection because no clearly defined method of locating detection has been developed.

Critics from private and public agencies often state that research efforts are largely wastes of time and money. While the results may produce enhanced transportation methods for estimating and predicting flows, they often rely on assumptions that are impractical and not easily accomplished in practice. Without the support and implementation by practitioners, the research does not contribute a service in providing a practical solution to a problem or aid in fulfilling a need.

Much research has focused on new ways of estimating, predicting, forecasting and a number of other terms used to represent scientific guessing of flows. But these models, while more efficient, are less accurate than actual detection. After years of emphasis on estimation methods, the computer processor and communication speeds are finally available to utilize actual detection information to truly optimize systems. It is hard to image a modeling tool that could provide traffic control, speed, or flow estimation from Origin-Destination information as accurately or reliably as from real-time detection. The purpose for estimation is necessary when detection is limited or unavailable. Through the rush to develop newer and more advanced estimation techniques, one critical issue is left relatively under investigated. Optimizing the use of detection to provide sufficient network flow information in the absence of saturation detector coverage would improve the likelihood that these new systems could be implemented. This research provides the insight into a method that allows detector locations to be assessed in a rigorous scientific way instead of the historic ad hoc methods.

REFERENCES

The majority of the references are sited in the literature review contained in the Stage Report. This reference list is only for this final analysis results document, therefore the sparse list. See the Stage Report for the detailed literature review reference list.

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APPENDICES