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DEVELOPING AN AREA-WIDE SYSTEM FOR COORDINATED RAMP METER CONTROL

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16. ABSTRACT

Ramp metering has been broadly accepted and deployed as an effective countermeasure against both recurrent and non-recurrent congestion on freeways. However, many current ramp metering algorithms tend to improve only freeway travels using local detectors' inputs and overlook the negative impacts on local streets. This may generate two problems: 1) the optimal local settings may not result in a system-wide optimum in terms of traffic operations; and 2) the increased congestion on local streets due to on-ramp overflow may counteract the gains in freeway operations. To address these problems, we propose an area-wide ramp metering system to improve the coordination of ramp meters for system-wide optimization and on-ramp overflow minimization. Our experimental results show that our method can offer improved performance in ramp metering operations under tested scenarios and also reduce the likelihood of on-ramp overflow.

This novel strategy for active ramp metering is inspired by the principles of a computer network congestion control strategy. In this strategy, certain types of congestion at a targeted freeway location can be significantly reduced by limiting on-ramp vehicle flows to a fraction of ramp demand and then additively increasing rates to avoid ramp queue spillover onto city streets. This approach can be actively used to immediately curb the growth of traffic congestion and therefore shorten travel delays. The effectiveness of this ramp metering approach has been evaluated by microscopic simulation experiments. Our experimental results show that our method can reduce system-wide travel delays in the tested scenarios by as much as 28.2% when compared with the Fuzzy Logic ramp metering algorithm, and also reduce the frequency and severity of on-ramp overflow. This indicates that this area-wide algorithm can provide benefit when applied to urban freeway corridors for congestion mitigation.

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EXECUTIVE SUMMARY

Throughout the United States, the growth of traffic demand on freeways has far outpaced the growth rate of constructed lane miles. This widening gap between travel demand and infrastructure supply has resulted in an increase in congestion levels. Within the Seattle, WA area, this has translated to over 70 million hours of travel delay and over 45 million gallons of excess fuel consumption at a cost of over $1 billion. Given high construction costs and impacts, one accepted way to address these problems is to manage the existing infrastructure more efficiently with traffic control and management technologies such as ramp metering. Studies performed within the Seattle area at the introduction of new ramp metering methodologies have shown coincided significant reductions in travel time as well as lower accident rates.

Ramp metering breaks up long strings of vehicles merging onto the freeway and controls the freeway demand. Outcomes of these actions include a reduction in secondary queuing within the merging area and a reduction of congestion within the downstream mainline portion of the freeway. The simplest ramp metering methods are pre-timed and are mainly beneficial for recurring congestion such as predictably heavy rush-hour traffic. Since most congestion is nonrecurring, such as congestion caused by accidents on the freeway, dynamic algorithms that use live traffic data from on-site sensors provide more benefit.

In looking at existing ramp metering algorithms, we observed that some algorithms incur a long start-up time—the critical time that optimal adjustment is given to current traffic conditions. Additionally, most algorithms we surveyed do not

proactively reduce the chance of vehicle spillover onto city streets, and do not explicitly use ramp storage capacities to intentionally reduce mainline congestion.

We have designed a new ramp metering algorithm that addresses these issues. It is inspired by the Additive Increase Multiplicative Decrease (AIMD) congestion control mechanism used in the field of computer networking. In our algorithm, a series of upstream on-ramps are selected to be metered at a multiplicatively reduced rate to regulate mainline traffic flow to the reduced capacity caused by congestion. Then, ramp metering rates are additively increased to the initial ramp demand; the rate of increase is set to fill ramps to a prescribed storage capacity while avoiding overflow in a designated time period. To continue addressing the remaining capacity deficit, additional upstream ramps are selected for metering, repeating the multiplicative/additive process.

To test this algorithm, we implemented two models of Seattle area freeways—Northbound I-5 in northern Seattle and Westbound I-90 in Bellevue and Issaquah within the PTV Vision VISSIM microscopic traffic simulator. We also implemented the currently active Fuzzy Logic ramp metering algorithm per Washington State Department of Transportation specifications and consultation as a benchmark algorithm. Our scenarios consisted of lane-blocking incidents during both peak-period and non-peak period traffic conditions modeled from two midweek days in August, 2006.

We found in our experiments that our AIMD method outperformed the Fuzzy Logic algorithm in most cases, offering reduced system-wide delay and improved mainline travel. In particular, AIMD significantly reduced the average systemwide vehicle delay by as much as 28.2%. In one scenario, AIMD reduced ramp spillover into surface streets that was otherwise observed with Fuzzy Logic. In this scenario, systemwide total delay was reduced by 5.4% from that of Fuzzy Logic.

Through our research efforts, we identified a selection of improvements that can be made to our algorithm and our models, as well as additional criteria that would be valuable for new experimental scenarios. Our recommendations are to conduct further research to address these improvements and to develop the algorithm for eventual on-site testing.

1 INTRODUCTION

From 1980 to 2005, yearly vehicle miles traveled in the US increased by 95.4% from 1.53 million to 2.99 million, while road mileage increased only about 3.5% from 3.86 million miles to 4.00 million miles (Bureau of Transportation Statistics, 2007). The enlarging gap between travel demand and infrastructure supply has increased the level of congestion nationwide. According to the 2007 Urban Mobility Report (Schrank and Lomax, 2007), the annual average delay per person in the 85 surveyed-urban areas was 44 hours in 2005, a 175% increase compared to that of 1982. The Greater Seattle area has consistently been ranked as one of the most congested areas in the United States. Traffic congestion resulted in a total of 74.1 million person-hours of travel delay and 54.7 million gallons of excess fuel consumption in Seattle in 2005, which correspond to a congestion cost of $1.41 billion, the 15th highest in the U.S. (Schrank and Lomax, 2007).

Adding more roadways and lane capacity have been traditional solutions for solving traffic congestion problems. However, due to the high construction costs, long project cycles, and complicated procedures for new construction projects, the increase of roadway mileage has lagged far behind the increase of demand over the past several decades. A commonly accepted solution to address the gap between roadway supply and travel demand is to manage the existing infrastructure more efficiently with traffic control and management technologies. Of these technologies, ramp metering has been regarded as the most direct and efficient countermeasure against freeway congestion (Papageorgiou et al, 2003). Since the ramp metering concept was introduced in 1960s, ramp meters have been deployed across the country and proven to be effective for freeway congestion management (Bogenberger and May, 1999).

Ramp meters are stop-and-go signals located on entrance ramps of freeways. They are intended to improve traffic conditions on freeways by regulating how quickly vehicles can join the mainstream traffic. This can bring about two outcomes: the reduction of secondary queuing within on-ramp merge areas caused by vehicle platoons, and the reduction of vehicles contributing to mainline congestion. Ramp meters also have the capacity to distribute demand among multiple on-ramps, discourage short trips, and encourage the use of underutilized ramps and arterials (Jacobson et al, 1989).

Ramp metering strategies can be divided into two categories: pre-timed meter control and traffic responsive meter control. Pre-timed ramp metering is very similar to pre-timed intersection signal control. It does not rely on live traffic data. Parameters are predetermined based on off-line analysis with historical data. For this reason, pre-timed ramp meter control is only effective for recurrent congestion (Saito et al, 2003). Since nearly 60% of traffic delays are caused by non-recurrent congestion (Cambridge Systematics Inc., 1990), pre-timed ramp meter control effectiveness is largely degraded in typical freeway applications. To address this problem, traffic responsive ramp meters have been developed and deployed. These ramp meters use real-time traffic detector data for meter rate calculations and are therefore responsive to both recurrent and non-recurrent congestion.

The effectiveness of traffic responsive ramp meters has been verified by several studies. For example, Piotrowics and Robinson (1995) reported that Seattle's FLOW ramp metering project that applied the Bottleneck algorithm (Jacobson et al, 1989) reduced freeway travel time from 22 min to 11.5 min and decreased accident rates by 39% in the metered area. The Fuzzy Logic ramp metering algorithm (Taylor and

Meldrum, 1998) currently employed by the Washington State Department of Transportation (WSDOT) outperformed the bottleneck algorithm in a test conducted by Taylor and Meldrum (2000b). Depending on the designs of traffic responsive ramp metering algorithms and characteristics of the roadway networks in which they are deployed, actual benefits can vary significantly from case to case.

1.1 PROBLEM STATEMENT

In order to operate a freeway according to particular goals in efficiency and to create minimal impact on the operation of surrounding city streets and the overall delay experienced by drivers, it is important for ramp metering strategies to address a number of challenges that are found within existing systems. In particular, ramp metering strategies should allow for flexibility in configuration to meet a set of goals, and should provide safeguards against the overflow of traffic onto city streets. Furthermore, an ideal ramp meter strategy should address these goals with a proactive methodology, reducing the amount of startup time needed for discovering and properly addressing a problem such as an incident on the freeway, thus reducing the amount of congestion and delay experienced by drivers.

As seen in the next section, many existing strategies tend to be reactive rather than proactive. For example, a particular measure for reducing the chance of ramp queue spillover may only occur when a loop detector placed at the entry of a ramp detects high occupancies. Also, many strategies do not employ a methodology that intentionally uses the available ramp queue storage capacity for effecting an intended outcome; instead, the available capacity is not an explicit factor within such methodologies when real-time inputs are used to compute metering rates.

We address these two challenges through a novel approach for ramp metering that provides freeway operators an active control mechanism for immediately curbing the growth rate of delayed vehicles behind a targeted traffic-blocking incident or stationary choke point. This is accomplished by limiting incoming on-ramp traffic to a fraction of normal flow rates and then additively increasing metering rates while filling the ramps to a predefined capacity; hence, the mechanism is called AIMD (Additive Increase, Multiplicative Decrease). At this point, original throughput of the on-ramp is restored to avoid traffic spilling out beyond the ramp entrance. We find through simulation that for certain types of scenarios, our targeted response method offers a significant reduction in the delay of mainline traffic when compared with the Fuzzy Logic algorithm (Taylor and Meldrum, 2000a) that is currently deployed by the Washington State Department of Transportation (WSDOT) in the two sites that we have modeled.

2 REVIEW OF PREVIOUS WORK

A number of surveys, case studies, and implementation notes exist on ramp metering strategies (US Department Of Transportation Research and Innovative Technology Administration 2008) (Bogenberger and May, 1999). Many designs have been devised and implemented in urban locations since the introduction of ramp meters in the 1960s. We describe a selection of ramp metering algorithms to compare and contrast our work and also review some state-of-the-art examples of recent ramp metering research.

2.1 RAMP METER RESEARCH EMPHASES

2.1.1 Dynamic Congestion Response: ALINEA and METALINE

Two long-standing examples of ramp metering strategies that are responsive to traffic congestion are the ALINEA (Asservissement linéaire d'Entrée Autoroutière) algorithm (Papageorgiou et al, 1991) and its area-wide variants as METALINE (Papageorgiou et al, 1990). These approaches have been demonstrated to be beneficial and stable to the freeway under certain traffic operation policies. The additive nature of the metering rate calculations inherent in these strategies, however, requires that several iterations be executed before effectiveness is achieved. This is undesirable, as the Mobility Facts (Lerner-Lam, 1992) state that traffic delays increase geometrically with increases in incident duration. Slow startup reduces the prevention of congestion and causes the most valuable time period for reducing total vehicle delay to be wasted. In our work, we seek to promptly start our response at an effective level when ramp meters are enabled.

ALINEA and METALINE estimate traffic density from occupancy measurements at loop detectors downstream of the metered on-ramp. The meter rate is adjusted according to a linear feedback control mechanism. One assumption inherent in the operational theory behind these algorithms is the preservation of freeway efficiency at the cost of unlimited delay imposed on incoming vehicles. This leaves opportunities for spillover onto surface streets and a decreased vehicle throughput on traffic entering the freeway. These aspects directly conflict with traffic operation policies that are designed to minimally impact surrounding roadway networks, as well as policies that provide an equitable level of service to traffic in close proximity to incidents.

2.1.2 Equity: BEEX

An important aspect of ramp metering is that of equity: balancing a ramp meter's congestion reduction capabilities with the delay experienced by drivers in varying proximities to congestion sites. Zhang and Levinson (2005) find that the strongest metering strategy possible—that of maximum reduction of mainline delay at a bottleneck site—imposes severe delay penalties on on-ramp traffic closest to the bottleneck. The most equitable metering strategy, on the other hand, is said to have the goal of allowing all drivers to experience the same average trip speed, regardless of their proximity to the bottleneck when entering the freeway. The BEEX (Balanced Efficiency and Equity) demonstration specifically evaluates optimization methods for maximizing equity while minimizing efficiency loss (Zhang and Levinson, 2005). An aspect of this involves nonlinearly weighing each vehicle's travel time with the ramp meter-induced delay while giving preferred treatment to those vehicles most affected by metering. In our system, it is possible to set ramp capacity variables to limit the maximum delay, but equity/efficiency optimization as seen in BEEX can provide superior guidance in optimizing these settings automatically, system-wide.

2.1.3 Prediction: SWARM

SWARM (System-Wide Adaptive Ramp Metering) uses data from detectors placed at bottleneck locations to estimate roadway densities. The system continuously applies a linear regression on recent Kalman filtered data to forecast rises in density. If the prediction exceeds a preset saturation density, a calculated number of vehicles necessary to prevent the oversaturation are withheld among upstream ramp meters. This system had recently been evaluated in the Portland, Oregon area (Ahn et al, 2007).

2.1.4 System Integration: MILOS

MILOS (Multi-objective, Integrated, Large-scale, Optimized System) uses a selection of advanced computational techniques and a system communications architecture to negotiate interactions between freeway traffic and surface street signal control systems. The entire area-wide ramp metering operation is treated as a series of linear optimization problems that receive dynamically changing inputs from roadway detectors and traffic controllers. Ramp queue usage is calculated according to cost coefficients. Additionally, the system analyzes traffic patterns to predict appropriate strategies for alleviating impending congestion (Ciarallo and Mirchandani, 2002). MILOS is now being evaluated in an Arizona freeway corridor (Head and Mirchandani, 2006). Although our work is not as complex and general-purpose as MILOS, we anticipate that the MILOS system integration work can provide insight for scaling a system as ours.

2.2 RAMP METERING IN MINNESOTA

We briefly review the progression of ramp metering algorithms deployed in Minnesota to illustrate the effectiveness of new methodologies both on road network efficiency and also on public perception.

2.2.1 ZONE

The basic concept behind the Minnesota ZONE algorithm, in effect before the year 2002, was to control the volume of traffic passing through a series of roadway segments with the goal of keeping density at or below a constant value. These segments were usually allocated in such a way that the upstream ends carried free-flowing traffic and the downstream ends contained a critical bottleneck. One zone could span several off-ramps and metered on-ramps. The volume consistency was maintained by using ramp meters to make the sum of upstream volumes coming from mainline sources and controlled on-ramps equal to the sum of downstream volumes destined for off-ramps and reduced-capacity bottlenecks. (Bogenberger and May, 1999)

Although ZONE had been effective in reducing freeway congestion and accident rates, ramp meter-induced delays on on-ramps in excess of 4 minutes experienced by many drivers prompted the legislature to force all 430 Twin Cities-area ramp meters to be shut off for 6 weeks in 2000. The absence of metering was studied carefully, and results revealed several benefits that can be largely attributed to ramp metering. For example, during the period of no ramp metering, a 22% increase in freeway travel time and a 26% increase in crashes were observed. (Cambridge Systematics, 2001)

2.2.2 SZM

This prompted the development of a new ramp metering algorithm that improved upon safety and flexibility, but also imposed waits of no longer than 4 minutes. SZM (Stratified Zone Metering) characterizes freeway traffic conditions through the use of layers of segments. Unlike the single layer of segments found in ZONE, the SZM layers are hierarchical: the lowest layer contains zones that are defined by 2 contiguous stations, the next layer's zones each contain 3 contiguous stations, etc. This structure is hierarchically evaluated to meter on-ramp traffic to compensate for the excess demand found within all layers, determining system-wide metering rates according to downstream zones, ramp queue length, and maximum allowable ramp delay (Xin and Horowitz, 2004).

Further research is underway in estimating accurate queue sizes given inaccuracies in detection technologies employed (Liu et al, 2007). Most ramps in the Twin Cities area are equipped with queue and passage loop detectors—the queue detector being found toward the start of the ramp and the passage loop being found toward the end. These pairs of loops are used in SZM as check-in/check-out detectors to keep a count of ramp meter queue length. This check-in/check-out conservation methodology produces erroneous queue length estimations if one or both of the loops do not count accurately. Liu et. al. (2007) proposes that ramps equipped with only an accurate queue loop detector use the ramp metering rate to substitute bad passage detector counts. For ramps with inaccurate counts from both the queue and passage detectors, a Kalman filtering model is applied to improve accuracy. Since we currently use similar check-in/check-out counts in our algorithm, this work is of interest for long-term robustness.

2.3 RAMP METERING IN WASHINGTON STATE

2.3.1 Bottleneck

The WSDOT commissioned the development of the Bottleneck algorithm in 1978 for use in the Seattle area. Bottleneck was designed within a framework that uses two algorithms—an independent and integrated algorithm—to generate two metering rates; the more restrictive rate was selected as the implemented rate. While the independent algorithm (called the Local Algorithm) consisted of using a curve to derive a predetermined metering rate from loop detector occupancies in the freeway mainline upstream of a metered on-ramp, the integrated Bottleneck algorithm had a broader area of impact (Jacobson et al, 1989).

For each segment often consisting of an upstream on-ramp and downstream off-ramp, Bottleneck compares the occupancies of detectors against threshold values that represent the freeway operating at capacity. For each segment satisfying this threshold, similar segment-based volume entry/exit metrics as employed as seen in ZONE to quantify the excess demand that must be controlled upstream through metering. While the segments employed in Bottleneck are smaller than those of ZONE, a tunable number of upstream on-ramp metering rates outside of the each segment can be influenced via weighting factors. As a result, segments that contain recurring bottlenecks are configured to apply heavy weights to influence the on-ramp meter rates in the neighboring upstream segments (Jacobson et al, 1989).

As with the Minnesota shutdown study, freeway benefits were observed in the Seattle area that were at least partially attributed to the introduction of ramp meters. When ramp metering was introduced, the travel time in a 6.9-mile (11.1 km) site decreased by 43% in the first two years. And, among a 5-year pre-metering period ending in 1981 and a 3-year post-metering period beginning in 1985, a 38% decrease was observed in the number of accidents within the analyzed 12.4-mile (20.0 km) corridor (Jacobson et al, 1989).

2.3.2 Fuzzy Logic

The WSDOT later commissioned the development of a new ramp metering algorithm for the Seattle region that employed fuzzy logic, a means of comparing values in a qualitative fashion rather than by absolute, black-and-white metrics. This was done because of insufficiencies found in the Bottleneck and Local strategies employed up until 1999. Both Bottleneck and Local strategies performed poorly in the presence of inaccurate or malfunctioning loop detectors. Also, they caused oscillations in queue length and metering rate because of decisions within the algorithms activated by constant thresholds and the lack of inputs originating from other locations within the system (Taylor and Meldrum, 2000a). For these and other reasons including gradual changes in vehicle volumes in critical portions of freeway, Bottleneck required constant tuning (Taylor and Meldrum, 2000b). Poor detector layout was also a source of concern that could not be corrected by the older algorithms. Ultimately, Fuzzy Logic showed improved performance in the study sites, including a reduction of queue detector occupancy (a sign of shorter ramp queues), and much less oscillation of queue lengths. It was also observed that Fuzzy Logic produced metering rates that were more appropriate for given current traffic conditions than what was experienced previously.

The Fuzzy Logic algorithm currently deployed in the Seattle freeway network converts a variety of system-wide live detector input data into qualitative terms (e.g.

“very high”, “low”, etc.) These qualitative classifications for downstream occupancy, local speed, etc. are then weighed according to a set of rules and reformulated into a final metering rate. For each meter, inputs for these rules include mainline speed and occupancy at each metered on-ramp, the maximum occupancy and speed found among a selected set of downstream loop detector stations, and occupancies at detectors placed toward the entry end of the on-ramp (Taylor and Meldrum, 2000a). This general-purpose, qualitative system is reportedly straightforward to configure for a particular location and is robust to imprecise or missing detector data (Taylor and Meldrum, 1998).

Our algorithm differs from Fuzzy Logic in several regards. Our algorithm is explicitly instructed where an incident is located and monitors the growth and dispersal of congestion, whereas traffic operations personnel manually enable and disable Fuzzy Logic metering on groups of ramps in response to incidents (unpublished data). We have designed our algorithm to deliberately use all permitted ramp storage capacity to effect an intended outcome—congestion reduction at the site of the incident—whereas Fuzzy Logic does not bear such an explicit definition for ramp storage space usage. Fuzzy Logic therefore may not exert a desired degree of traffic control in as many scenarios because it reacts only to inputs from a limited number of roadway sensors. A consequence of this in worst-case scenarios is that traffic can overflow onto city streets—a politically undesirable outcome that causes problems in city traffic operations (Jacobson et al, 1989). While our algorithm’s meter rate is additively adjusted to avoid such spillovers, Fuzzy Logic reactively accelerates its metering rate when detectors placed toward the end of the on-ramp are occupied by waiting vehicles. In light of these observations, we have observed that no amount of ramp metering can improve the worst cases of traffic congestion.

Because our modeled freeways currently use the Fuzzy Logic algorithm, we have chosen to implement Fuzzy Logic within our models as a benchmark algorithm for our experiments.

3 METHODOLOGY

A search on the Internet for the keywords “traffic congestion control” presents results that mostly pertain to computer network congestion rather than roadway network congestion. But, computer network congestion control theories may be applicable to roadway networks with appropriate modifications, offering new ways to envision roadway traffic management. The Additive Increase Multiplicative Decrease (AIMD) congestion control mechanism (Chiu and Jain, 1989) employed by Transmission Control Protocol (TCP) networks provides one such inspiration. It is through this concept that we have developed an area-wide system for coordinated ramp meter control and focused upon its applicability for addressing freeway congestion.

3.1 ADDITIVE INCREASE, MULTIPLICATIVE DECREASE

The AIMD mechanism is primarily intended to address computer network congestion promptly by setting the entering network traffic rate to a level that is sufficiently low to avoid further deterioration of network traffic flow. This concept is also important for roadway traffic networks because traffic queues can form quickly at bottlenecks but take much longer to discharge.

The AIMD mechanism is applied to a coordinated ramp meter group using a two-step algorithm. First, the upstream on-ramps that are to be metered are selected as seen in Figure 3-1; the criteria for selection are based upon the measurements of reduced capacity. Then, the ramp metering rates at each ramp are systematically set as shown in Figure 3-2. Details of the two steps are described in Sections 3.2 and 3.3.

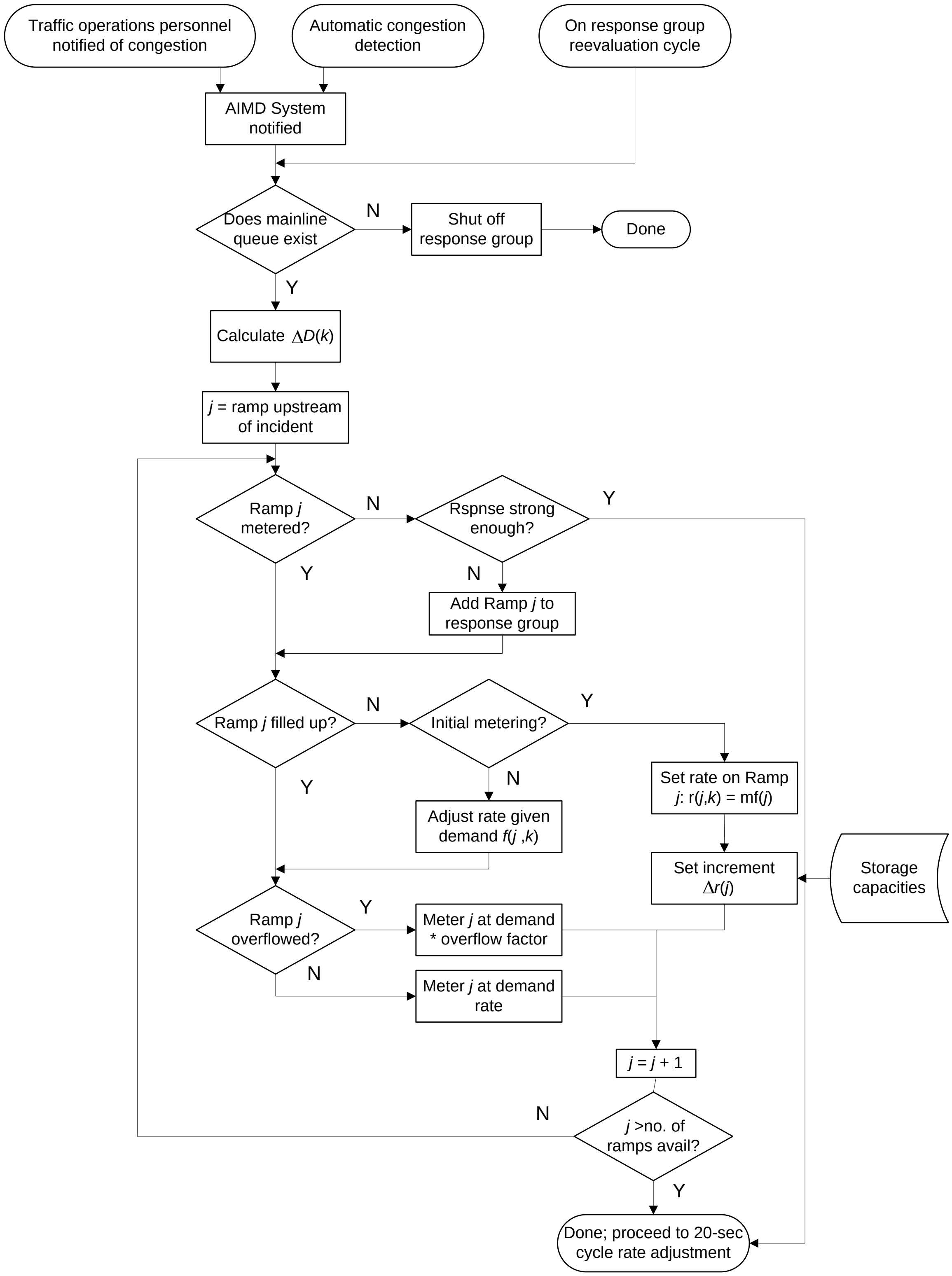


Figure 3-1. AIMD algorithm response group flowchart

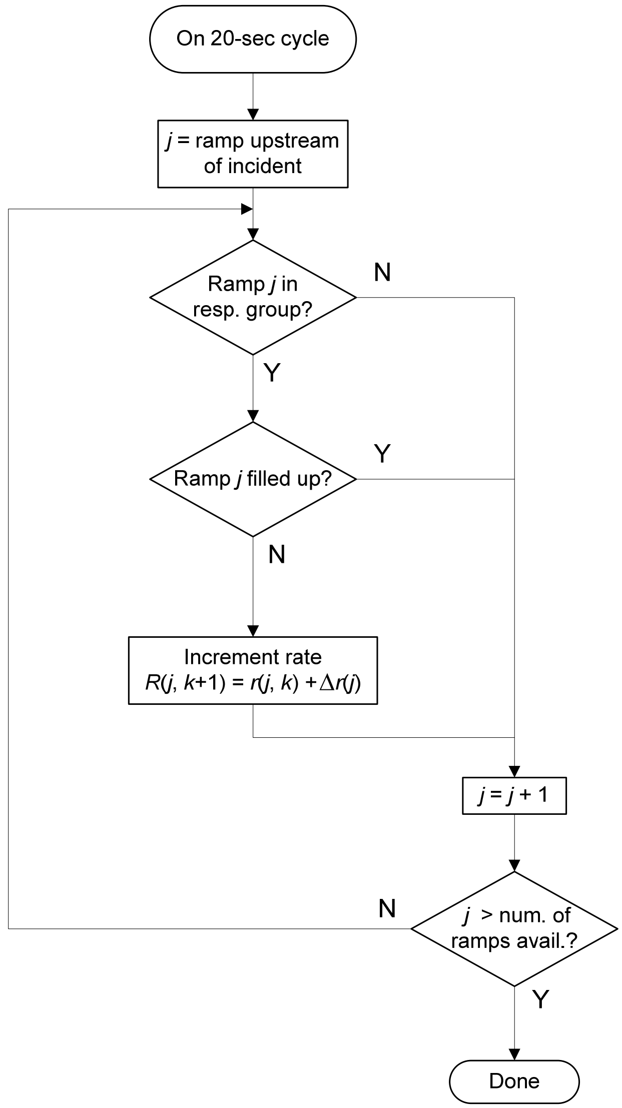


Figure 3-2. AIMD algorithm metering rate flowchart

3.2 RESPONSE GROUP ASSEMBLY

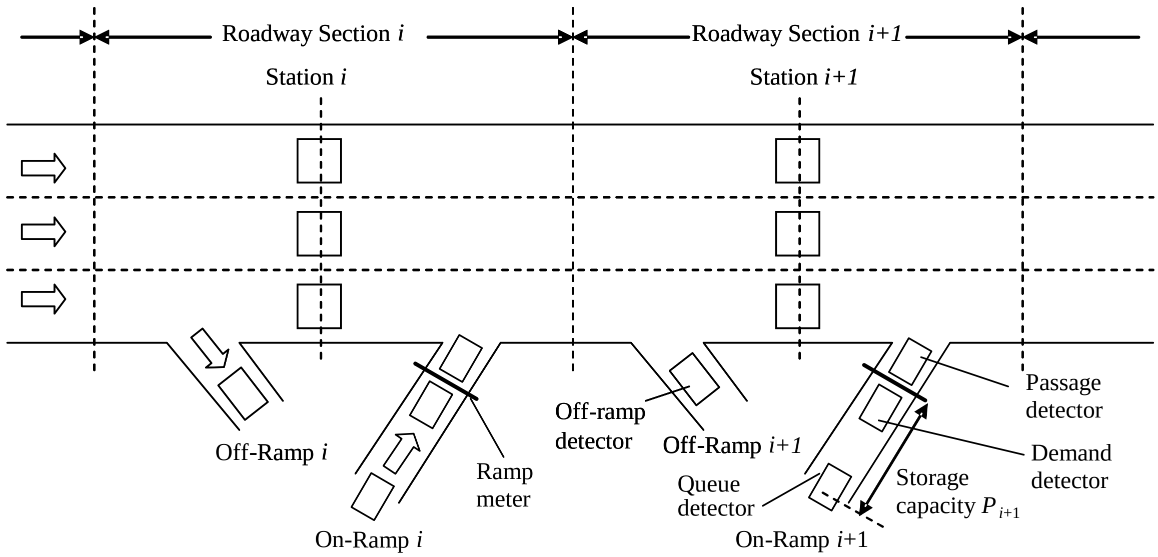


Figure 3-3. Freeway layout example

Figure 3-3 shows a section of typical freeway layout. Our assumptions concerning segments are that segments are bounded by loop detector stations. Typically, loop detector stations are around half a mile (0.8 km) apart and contain at most around half of an interchange on each end.

In selecting the response group—the contiguous pool of upstream ramps that are metered to mitigate a particular area of downstream congestion—it is helpful to propose that an incident such as a lane-blocking disabled vehicle exists between Stations *i* and *i* + 1 in Figure 3-3. Here, the upstream traffic flow from the mainline and on-ramps (if any) at Station *i* represents the demand. In addition, the eventual downstream mainline and off-ramp traffic flow found at Station *i* + 1, if less than the traffic flow at Station *i*, is a consequence of the reduced capacity caused by the incident and growing vehicle density behind it.

Let us define k to be the time that the incident location is made known to the ramp metering system so that a response group can be established. We also assume that time interval k occurs after the start of the incident at time interval k_0. In our experimental system, each time interval is 20 seconds, the length of time used by WSDOT sensors for reporting periodical measurements.

Two variables are estimated and used to establish the response group: the number of vehicles queued behind the bottleneck or incident, and a measure of the excess demand given the reduced capacity imposed by the congestion.

3.2.1 Vehicle Queue Estimation

We must determine an approximation of the number of vehicles that are queued up behind the incident location at time interval k to establish an appropriately-sized initial response group. Our approach is to quantify the number of vehicles within a roadway segment. This can be done by counting the number of vehicles that leave each segment on the downstream end for a sufficient amount of time and subtract this from the count for entering vehicles on the upstream end of the same segment. Specifically:

$$Q(i,k) \approx \sum_{x=k_0+1}^{k} V_{in}(i,x) - \sum_{x=k_0+1}^{k} V_{out}(i,x) \tag{1}$$

where

V_{in} is the volume of traffic entering the upstream end of Station i in vehicles per time interval, with corresponding on-ramp volumes included, and

V_{out} is the volume of traffic leaving the downstream end of Station i, with corresponding off-ramp volumes included.

The time between time intervals k_0 and k should be long enough to represent typical free-flow travel time under incident-free conditions from one end of the segment that contains the incident to the other.

If congestion is detected promptly, Q should be small. At each successive time interval, Q can be updated by performing:

$$Q(i,k+1) \approx \sum_{x=k-w+1}^{k} V_{in}(i,x) - \sum_{x=k-w+1}^{k} V_{out}(i,x) \tag{2}$$

where

w is the number of intervals between queue size estimation measurements. In our model, w = 3. A value that is greater than 1 provides a greater degree of stability in measurements.

3.2.2 Excess Demand Estimation

If $Q(i, k)$ and $Q(i, k_0)$ are approximately equal given typical fluctuations in normal traffic flow, then traffic density between the incident location and Station i is not increased between intervals k and k_0. This implies that the reduced capacity caused by the incident is still sufficient to handle the demand and that on-ramp control is not necessary. However, if $Q(i, k)$ is significantly higher than $Q(i, k_0)$, then excess demand is witnessed and on-ramp metering is necessary.

The excess demand over the reduced capacity, denoted by ΔD in vehicles per time interval, represents the upstream demand that exceeds the reduced capacity at the incident location. Assuming that the vehicle volumes observed at Station i + 1 are limited by the reduced capacity at the site of the incident, ΔD can be estimated as:

$$\Delta D(i,k) \approx \frac{\sum_{x=k-a}^{k} V_{in}(i,x) - \sum_{x=k-a}^{k} V_{out}(i,x)}{a} \tag{3}$$

where

a is the number of time intervals to sample in acquiring a stable excess demand estimation. In our experiments incorporating a 2-minute startup delay, we have empirically found $a = k - k_0$ to produce reasonable results for ΔD. In our simulations, smaller values of a have resulted in less stability.

3.2.3 Automatic Segment Extension

In the worst types of congestion, the queue can extend beyond the upstream end of the segment in which it originates. To have better measures of queue size and excess demand, it is then necessary to track the queue into the upstream neighboring segment. An automated comparison of density and speed can be used to notify the system of the need to extend the segment.

Traffic volume V, space-mean speed $\bar{s}$, and traffic density d are three fundamental variables in traffic flow theory and hold the following relationship:

$$V = \bar{s} \cdot d \tag{4}$$

Traffic density has been used as the sole variable for freeway Level of Service (LOS) analysis (Transportation Research Board, 2000). However, using the density alone for congestion detection may result in frequent false alarms because even when d is high, throughput can remain high as long as traffic flow does not enter a breakdown, low-speed condition. As has been observed in practice, $\bar{s}$ is low and d is high when congestion occurs.

Our models assume the use of loop detectors. Assuming vehicles travel at a constant speed over each roadway section, the occupancy of interval k at station i can be related to vehicle length and speed as:

$$O(i,k) = \frac{\sum_{x=1}^{N(i,k)} \frac{l_x}{s_x}}{T} \tag{5}$$

where

k is the time interval index,

i is the roadway section index,

N is the number of vehicles counted for the interval,

x is the vehicle index among all counted vehicles,

s is vehicle speed for each vehicle,

l is the effective length for each vehicle, roughly equal to the sum of vehicle length and loop detector length,

T is the length of time interval, and

O is the loop measured occupancy.

Since we assume that all vehicles travel at approximately a constant speed $\bar{s}(i,k)$, then Equation (5) can be rewritten as

$$O(i,k) = \frac{N(i,k) \cdot \bar{l}(i,k)}{\bar{s}(i,k) \cdot T} \tag{6}$$

where

$\bar{l}$ is the mean effective vehicle length. We use $\bar{l} = 18\,\text{ft}$ (5.5 m) in our calculations based on the study by Wang and Nihan (2003).

Since hourly traffic volume *V(i,k)* = *N(i,k)/T*, using *V(i,k)* to replace *N(i,k)/T* yields

$$O(i,k) = \frac{V(i,k)}{\bar{s}(i,k)} \cdot \bar{l}(i,k) \tag{7}$$

Comparing Equation (7) with Equation (4), we can obtain

$$d(i,k) = \frac{O(i,k)}{\bar{l}(i,k)} \tag{8}$$

Consequently, space-mean traffic speed can be calculated as

$$\bar{s}(i,k) = \frac{V(i,k) \cdot \bar{l}(i,k)}{O(i,k)} \tag{9}$$

Given high signal to noise ratios found in occupancy measurements, it is ideal to use speed trap detectors to supply $\bar{s}$, as we have done in our models.

If

$$d(i,k) > d_{cr} \tag{10}$$

and

$$\bar{s}(i,k) < s_{cr} \tag{11}$$

then congestion is detected. Here d_{cr} is a pre-specified critical density value (in our model: 50 vehicles per mile, or 31 veh/km) and s_{cr} is a chosen critical speed value (in our model: 40 miles per hour, or 64 km/h). Selections of these thresholds are based upon observations of volume-density relationships in (Drake et al, 1967).

Once congestion is detected on a segment boundary, the vehicle volumes from the new, upstream segment are incorporated into mainline queue estimations by superseding Equation (2) with:

$$Q(i,k+1) \approx \sum_{y=i-E}^{i} \left(\sum_{x=k-r+1}^{k} V_{in}(y,x) - \sum_{x=k-r+1}^{k} V_{out}(y,x) \right) \tag{12}$$

where

E is the number of segment extensions to be incorporated. In our model E is not extended beyond 1. While it is possible to proceed beyond one extension, we did not perform any tests with this, primarily because of the propagation of inaccuracies that would be likely found in live loop detector measurements. More on this issue and consequences of this limitation are discussed in Section 3.5.3.

Other variables as defined in Equation (2). Similar changes are made to Equation (3) for ΔD.

3.2.4 <u>Response Group Size</u>

If ΔD can be controlled to be less than 0, the growth of the queue can be reversed. To approach this goal, we can meter ramp traffic in an ordered fashion so that the total blocked on-ramp demand in an interval is no smaller than ΔD. Based on the AIMD mechanism, the initial ramp metering rate *r* for an on-ramp *j* is set at a fraction of the on-ramp demand:

$$r(j,k) = m \cdot (F(j) - H(j)) \tag{13}$$

where

m is the multiplier coefficient that is between 0 and 1, and

F is the total on-ramp demand in vehicles per time interval. On-ramp demand should be a stable value measured over a span of time greater than 3 min., or considered constant. In our model, it is 10 min., measured from the advance queue detector placed at the entry of the on-ramp.

H is the flow rate of HOV vehicles using the ramp's HOV bypass in vehicles per time interval, or 0 if no bypass exists. In our model, *H* is sampled similarly as *F*, but is measured from the HOV passage detector. This change in position from the on-ramp's entry point guarantees that measured vehicles are only HOV vehicles.

For clarity, we shall define $f = F - H$, where f is the on-ramp demand for non-bypassed vehicles. Equation (13) then becomes:

$$r(j,k) = m \cdot f(j) \tag{14}$$

Suppose n upstream on-ramps should be included in the response group. The total blocked vehicles for interval k is then expected to be

$$\sum_{j=i-n}^{i} (f(j) - r(j,k)) = (1-m)\sum_{j=i-n}^{i} f(j) \tag{15}$$

The total blocked vehicles for interval k should satisfy

$$\sum_{j=i-n}^{i} (f(j) - r(j,k)) \geq \beta \cdot \Delta D(i,k) \tag{16}$$

or

$$\sum_{j=i-n}^{i} f(j) \geq \frac{\beta \cdot \Delta D(i,k)}{1-m} \tag{17}$$

where

β is a coefficient with a value no less than 1.0. If a higher β value is chosen, then a stronger response will be initiated and a bigger response group will be established. This coefficient affects the proportion of emphasis given to the efficient flow of mainline, uncontrolled traffic versus the efficiency of traffic that enters the freeway through metered on-ramps.

Since the constrained upstream traffic takes time to arrive at the congestion area, the accumulation of delayed vehicles in the congestion area may increase over a certain time period after ramp metering is started and then decrease until the congestion is fully discharged or all possible available ramp capacity is exhausted.

In this derivation we assume all vehicles entering the freeway through ramps in the response group are destined toward the incident site. In reality, this is not necessarily true; drivers penalized by ramp metering while entering the freeway may exit before encountering the incident site. Depending upon origin-destination travel patterns within a particular geographic region, the estimation of the number of ramps needed within the response group according to (17) may be too low. Furthermore, to prevent excess delay caused by a large response group, the extent of the response group may need to be limited.

In our simulations, an assigned ratio of vehicles exit at each diverge point regardless of each vehicle's origin. Our simulations therefore represent an unfavorable origin-destination travel characteristic, introducing more systemwide delay and less congestion control than what might be otherwise experienced if more vehicles stay on the freeway longer after entering. Ideally, this systemwide delay can be reduced by incorporating relevant origin-destination travel patterns for the region into the model; in our case, however, these patterns were unknown.

3.2.5 Response Group Recurring Reevaluation

As seen in the Figure 3-1 flowchart, response group assemblies are recomputed periodically throughout the duration of the congestion to respond appropriately to short-term changes in ΔD and ramp demand. It is also possible to only recompute response group assemblies when ramp queues fill up, but in our experimental system, we find a slight improvement in performance when response groups are recomputed once every minute. We attribute this improvement in performance by the need for our algorithm to be adaptive toward stochastic vehicle arrivals to the ramp meter queue.

To facilitate the recomputing of response groups during the course of on-ramps filling, it is necessary to incorporate the current number of queued vehicles in each ramp to estimate the number of vehicles that can still be withheld. Equation (17) is correspondingly updated as follows:

$$\sum_{j=i-n}^{i} f(j) \geq \frac{\beta \cdot \Delta D(i,k)}{1-\left(m+\frac{(1-m)\cdot U(j)}{P(j)}\right)} \tag{18}$$

where

U is the number of vehicles already queued in the respective on-ramp, and

P is the usable ramp storage capacity.

3.2.6 <u>Ramp Queue Counting</u>

U, the number of vehicles in an onramp queue, is found by maintaining running counts of vehicles that pass through the advance queue detectors and the passage detectors. While this method for counting vehicles can prove to be problematic as seen in Minnesota (Liu et al, 2007), we use it in simulation with the expectation that it can eventually be replaced by a suitable estimation method.

With the current check-in/check-out scheme employed within our model, many ramps do not allow for clear distinction between HOV vehicles and single-occupant vehicles. Some ramps have a single advance queue detector before the HOV bypass lane is available. Other ramps equipped with longer HOV bypass lanes have suitably-placed advance queue detectors, but vehicles are free to change lanes after passing over the detectors. As a result, the ramp queue counts include those vehicles that are bypassing the queue on the HOV lane. At times of busy HOV bypass activity, the estimations on queued vehicles may be artificially low. Due to the higher speed of vehicles in the generally short bypass lane, a maximum of one or two vehicles affects the queue length estimation at any one time.

3.3 RAMP METERING RATE CALCULATION

The initial restrictive rate for ramp meter *j* is set at a multiple *m* of the on-ramp demand as shown in Equation (14). Thereafter, the rate increases additively from interval to interval with the goal of avoiding ramp queue spillover onto local streets. The increment for ramp meter *j* depends on how many vehicles the ramp can store. Our intent is for the ramp meter rate to reach the nonrestrictive level (the initial on-ramp demand) when the ramp is filled to its safely usable storage capacity *P*. When considering the value *P* for each ramp, spare capacity for sporadic peak arrival patterns should be factored. *P* also directly affects the maximum delay experienced by each driver and can be limited accordingly.

If it takes *u* intervals for the initially restrictive metering rate $m \cdot f$ to reach on-ramp demand *f* that is subject to metering (measured in units of vehicles per interval), *u* can be calculated as

$$u = \frac{f(j) - m \cdot f(j)}{\Delta r(j)} \tag{19}$$

where

$\Delta r(j)$ is the interval increment for on-ramp *j*.

The total blocked vehicles should be equal to the safely usable storage capacity *P* after *u* intervals. We find the value of $\Delta r(j)$ that achieves this goal through the use of arithmetic progression, where the sum of all evenly-spaced values a_1 through a_u over *u* increments is

$$sum = \frac{a_1 + a_u}{2} \cdot (u+1) \tag{20}$$

In summing the traffic demand that is restricted by the ramp meter, we get:

$$P(j) = \frac{((f(j) - mf(j)) + (f(j) - f(j))}{2} \cdot \left(\frac{f(j) - mf(j)}{\Delta r(j)} + 1 \right) \tag{21}$$

Rearranging terms for Equation (21) yields

$$\Delta r(j) = \frac{f^2(j) \cdot (1-m)^2}{2P(j) - (1-m) f(j)} \tag{22}$$

On-ramps with smaller storage space and larger demand will have a larger increment than those with a larger storage space and lower demand. From the initial rate set as seen in Equation (14), the metering rate is incremented at each interval by Δr. (As mentioned earlier, the interval used in our model is 20 sec.)

$$r(j, k+1) = r(j, k) + \Delta r(j) \tag{23}$$

3.3.1 AIMD and Prior Queuing

Under some circumstances, it is necessary to assume that a queue may already exist within an on-ramp when it is added to the response group. In particular, when a ramp is removed from a response group and undergoes a shutdown procedure (see Section 4.5.5), vehicles may still be queued in the event that the ramp is re-added.

In cases where AIMD must account for vehicles already queued, it is necessary to incorporate the number of queued vehicles into the Equation (14) calculation of initial metering rate. Equation (14) can then be updated as:

$$r(j, k) = f(j, k) \cdot \left(m + \frac{(1-m) \cdot U(j, k)}{P(j)} \right) \tag{24}$$

3.3.2 Demand Rate Tracking

Equations (14) and (22) for r and Δr, respectively, are formulated under the assumption that the ramp demand, *F*, is constant. It may be necessary to assume the ramp demand changes over time, making dependent variables as r and Δr require adjustment at predefined intervals to better match the most current ramp demand measurements. When the ramp metering rate is to be updated, the ramp meter rate can be calculated according to Equation (24), and Δr can be recalculated as in Equation (22) with the most recent ramp demand rate sampled over a period of time.

In our model, we update r and Δr in this way once every minute, letting Equation (23) be evaluated at the remaining 20-second intervals.

3.3.3 Rate Limits

An upper and lower limit may be placed on the output metering rate. An upper limit on rate is needed to prevent the ramp meter signal from oscillating between red and green too quickly. An upper limit that produces a cycle time of around 3 seconds is therefore desirable; the maximum meter rate is limited to 1160 vehicles per hour as in the WSDOT Fuzzy Logic algorithm specifications (Taylor and Meldrum, 2000a).

Likewise, a lower limit on rate directly affects the maximum possible delay experienced by drivers in the ramp meter queue and reduces the likelihood of ramp meter violations (Cambridge Systematics 2001). The Fuzzy Logic default parameters state the maximum cycle time as 19.3 seconds, or a minimum rate of 187 vehicles per hour (Taylor and Meldrum, 2000a).

When evaluating Equations (14) and (17), it is important to consider these limits as they can ultimately affect the number of vehicles that can be withheld on each ramp.

3.3.4 Ramp Queue Overflow Correction

The additive rate adjustment methodology employed in the AIMD algorithm is designed to fill ramp queues to a predefined capacity. Although extra space within the ramp may be allocated to accommodate unexpected rises in demand, this may not be enough to prevent overflow in all cases. When overflow absolutely must be prohibited, a feature similar to that found in SZM (Xin et al, 2004) and Bottleneck (Jacobson et al, 1989) is employed to temporarily increase the ramp meter rate when the occupancy measured from the advance queue detector at the on-ramp entry is over a predefined threshold. In our experimental system, the ramp meter rate is multiplied by a factor of 1.33 when the ramp queue exceeds the safely usable storage capacity P plus a maximum allowed deviation. This value of 1.33 was found in initial simulation trial runs to satisfactorily limit spillover from sporadic demand increases; the value of 1.2 caused too weak of a response to effectively reduce spillover delay. The current system should be configured to minimize or eliminate the strength and frequency at which this overflow mechanism engages, as this negatively impacts the effectiveness of AIMD by letting additional vehicles enter the freeway.

3.3.5 Ramp Demand Measurements

The ramp demand measurements used to supply the variable F in Equation (13) come from vehicle counts taken at the advance queue detector. If the ramp queue overflows and backs over the advance queue detectors, the measured rate decreases. Without safeguards, the perceived demand is decreased and the ramp meter rate is correspondingly decreased. In the current implementation, this creates an undesirable vicious cycle that can produce more congestion on city streets.

To avoid this problem, ramp demand samples are only taken when the occupancy of the advance queue detector is less than a given threshold. In our experimental model, this threshold is 10%. The value of 10% was chosen based on the observation of occupancy values in free-flowing traffic. While this works for our experimental model, this is not an ideal solution because demand samples are not taken at times of unexpectedly high demand. Ideally, demand measurements should be obtained from sensors and systems surrounding the streets that are not as prone to the problems mentioned.

3.4 INPUT REQUIREMENTS

Our implementation of AIMD uses a variety of inputs that can be made available from roadway detectors. In particular, we assume that the detectors are the same type as found in our experimental model site: 6-foot by 6-foot (1.8m by 1.8m) inductor loops embedded in the roadway surface. These inductor loops can individually provide vehicle count information as well as occupancy measurements—an indication of how long one or more vehicles occupy that particular measured patch of pavement. A high occupancy can be an indication of congestion. Inductor loops placed in sequential pairs on each lane can be used to measure vehicle speed and vehicle length.

These are the detectors and inputs that AIMD uses:

- **Mainline detectors:**
    - Vehicle counts: check-in and check-out for mainline queue size estimation Q
    - Occupancy: for incident segment extension
    - Speed: for incident segment extension
- **Exit detectors:**
    - Vehicle counts: check-out for mainline queue size estimation Q
- **Advance queue detectors:**
    - Vehicle counts: Ramp demand estimation F

- Occupancy: Ramp demand sampling suspension.

- **Demand detectors:**
    - Occupancy: call for the signal controller
- **Passage detectors:**
    - Vehicle counts: Ramp queue check-out for queue length estimation *U*. Check-in for mainline queue size estimation *Q*. HOV bypass: estimate for HOV bypass demand *H*.

Some of these detectors are different than what exists today in the sections of freeway that we have modeled. In particular, we include the following additions:

- **Advance queue detectors in HOV bypass lanes:** In reality, advance queue detectors are generally only found in general-purpose lanes. Our AIMD implementation uses a ramp queue count check-in/check-out detector pair for all traffic entering the on-ramp.
- **Advance queue detectors in general-purpose lanes:** Not all ramps are actually equipped with advance queue detectors. Again, our AIMD implementation requires vehicle counts for queue measuring.
- **Mainline detectors that measure speed:** Dual-loop speed traps are only actually found in locations generally over 1 mile apart. While it is possible to estimate speed from single loop detectors using the technique described in (Wang and Nihan, 2003), these estimations can be high in variance. For the purposes of staging our experiments in a controlled environment, we prefer to provide low-variance data for our inputs.

3.5 FUTURE METHODOLOGY

3.5.1 AIMD Coexistence

Many ramp metering strategies are designed to reduce secondary queuing in on-ramp merge areas. One of the mechanisms that help the most with secondary queue reduction is the breakup of platoons—series of consecutive vehicles that are "dumped" onto an on-ramp from an adjacent signalized intersection (Bogenberger and May, 1999).

Since AIMD is designed specifically for reducing delay caused by nonrecurring congestion at a particular point on the mainline, it is not intended to run before or after the response group selection mechanism deems it necessary to turn on ramp metering. This, however, leaves the job of platoon breakup and other local ramp congestion mitigation unresolved under the AIMD algorithm alone. One solution is to allow AIMD to coexist with another ramp metering algorithm. For example, Fuzzy Logic can control metering rates; then, when a response group is established, AIMD can override all Fuzzy Logic metering rates within the response group to effect the necessary changes in vehicle flow to reduce the mainline congestion around a particular incident. When the mainline queue caused by the incident clears, the AIMD response group will be empty, AIMD will shut down, and Fuzzy Logic ramp meter rates will no longer be overridden.

This approach to coexistence can also be applied to multiple AIMD response groups. Currently, no research has been performed within this project on the presence of multiple response groups (e.g. the mitigation of multiple congestion sites within our models) or background ramp metering. It is possible for the most upstream response group to override metering rates generated within the next downstream response group that encroaches on the upstream congestion site.

3.5.2 Automatic Incident Discovery

The operational model of initiating a response group—informing the system of the presence of a new incident—comprises entering the segment of the incident into the system, as well as providing an estimate on how long the incident has existed. A recommended form of incident discovery involves drivers calling traffic centers using their cellular phones (Xia and Horowitz, 2005), and this is the form that we use within our experimental scenarios.

Ideally, this manual step of incident discovery can be automated. However, reliable automatic discovery of incidents has been an area of ongoing research and for robustness requires more advanced techniques than the procedure described in Section 3.2.3. For example, many challenges exist in automatic video-based detection (Shehata et al, 2008) and the proper classification of traffic conditions from sensor data (Ghosh-Dastidar and Adeli, 2006). It is important to consider that the quality of discovery, including reliability and location accuracy, depends upon the degree of traffic flow sensor coverage on the freeway.

3.5.3 End-of-Incident Shockwave Tracking

For isolated incidents at moderately busy times of the day—especially incidents that cause lane blockages—congestion is fairly localized to the site of the incident. At times closer to peak volumes, however, when the freeway is operating more toward critical capacity, any minor perturbation has the capability of generating congestion. Furthermore, congestion takes longer to clear.

One phenomenon that had repeatedly been observed in our simulations is the slow movement of congestion upstream in a giant aggregate shockwave when the incident is cleared. This shockwave may propagate past several roadway segments. The best response group-related action for this phenomenon may be to progressively remove downstream ramps from the response group as the shockwave propagates backward. Our current methodology, however, does not currently define a means for accomplishing this. Instead, the original section and the adjacent upstream segment (added because of the incident segment extension function) track the elevated volume within those two segments, but do not cause ideal response group action after the shockwave leaves those segments. Instead, the response group is liable to be made empty prematurely, removing AIMD ramp meter control before congestion is cleared.

4 EXPERIMENT DESIGN

4.1 PLATFORM

We have implemented our urban freeway models using the PTV Vision VISSIM microscopic traffic simulator (PTV Vision, http://www.ptvamerica.com/software.html). VISSIM provides the means to define roadways, driver behaviors, vehicle handling characteristics, and other representations of real-life transportation systems and to simulate all traffic flow according to a vehicle following model. VISSIM's most sophisticated driver behavior model is based on the work of Wiedermann (1991). VISSIM also has the capability of controlling signals through a proprietary scripting language called VAP (Vehicle Actuated Programming). We implemented AIMD and our benchmark algorithm, Fuzzy Logic, in VAP for controlling the virtual ramp meters in our model.

Each simulation run is seeded with a random number. Due to the chaotic nature of vehicle interactions in congestion, outcomes of individual runs can vary considerably. For this reason, all of our simulation results are averaged over 10 runs; 10 was assumed to offer an acceptable margin of error.

4.2 MODEL 1: I-5

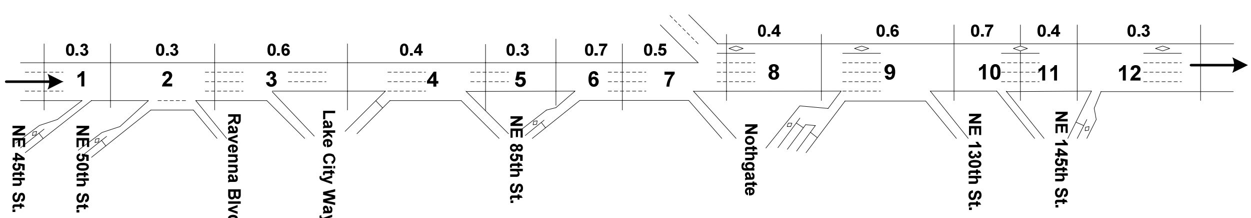


Figure 4-1. I-5 model segments

Our first model encompasses 5.6 miles (9.0 km) of northbound Interstate 5 from NE 45th St. past NE 145th St. in northern Seattle, WA. This region is informative for our preliminary tests because of the existence of 7 metered on-ramps and varying degrees of traffic densities that coincide with daily commuter patterns. In this modeled area, archived traffic flow speed measurements in 20-second intervals are available from 5 dual-loop detector stations, and volume/occupancy measurements of mainline and interchange locations are available from 8 additional loop detector stations. Interstate 5 in Seattle is well-equipped for automated traffic monitoring because of the inputs needed for the Fuzzy Logic ramp metering algorithm currently in operation, as well as other traffic reporting purposes.

As seen in Figure 4-1, this stretch of Interstate 5 varies from 3 to 5 lanes wide, including add-lanes from 2 on-ramps and exit only lanes to 2 off-ramps. The northernmost 2 miles (3.2 km) feature a left-side high-occupancy vehicle (HOV) lane. Of the 7 on-ramps, 5 of these have an HOV bypass lane that allows qualified vehicles to avoid the ramp meter queue. While the posted speed limit is 60 miles per hour (97 km/h), the free flow speed generally ranges from around 55 to 65 miles per hour (89 to 105 km/h). Note that the figure shows segment numbers on the roadway; each segment number corresponds with the detector station that is positioned at the segment's upstream vertical line. Each segment is also marked with its approximate length in miles.

The positions of the virtual loop detectors in our model are similar to those found on Interstate 5, including the mainline single-loop detectors and speed traps, advance queue detectors at the starts of each on-ramp, and presence/passage detectors at each signal head. We note, however, that positions are not exact. During the course of this research, we did not access resources that revealed precise loop detector locations, but we did find precise ramp meter locations. The need for precise loop detector locations was deemed a lower priority compared with other tasks at hand; it was assumed that the ultimate delay outcomes in simulation would not be significantly different.

To calibrate each of our test scenarios within the model, we chose Tuesday, August 8, 2006 for our tests due to the availability of sufficient 20-second data, the general absence of faulty loop detectors, normal driving patterns, and the minimal impact on traffic due to weather. (This day is reported to have been overcast). Our simulation model was calibrated following a similar approach introduced in Zhang et al. (2008). We calibrated our model by configuring driver behavior and speed distribution parameters so that modeled speed mean and variance resembled the 20-second loop detector speed trap data. We also specified vehicle distributions that mirrored the presence of heavy vehicles (based on vehicle length measurements in dual-loop detector data) and HOV vehicles.

We also observed that it was necessary to calibrate VISSIM virtual loop detector occupancy measurements to physical loop detectors installed in Seattle freeways. We found that comparable occupancy rates are produced by VISSIM when the virtual loop detectors on the I-5 model are configured to be 11 by 6 feet (5.8 by 1.8 m), as opposed to the 6 by 6-foot (1.8 by 1.8 m) actual detector sizes.

4.3 MODEL 2: I-90

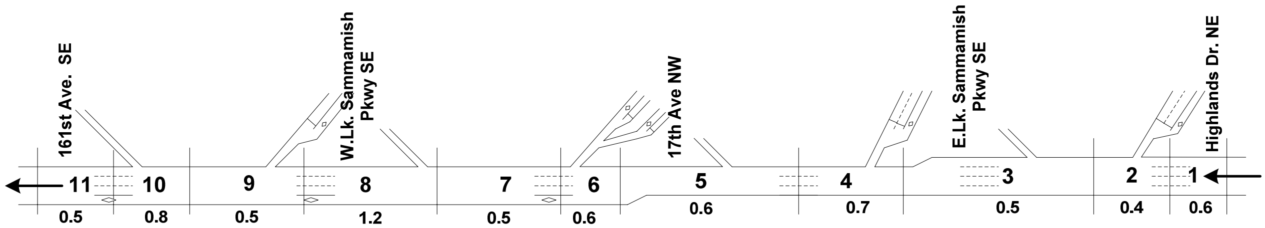


Figure 4-2. I-90 model segments

The second model consists of 6.7 miles (10.8 km) of westbound Interstate 90 from Highlands Dr. NE at the eastern end of Issaquah to 161st Ave. SE in the eastern part of Bellevue, WA. This portion of I-90 is also well-equipped with sensors, including 12 mainline stations as seen in Figure 4-2. Five of these can measure mainline speed. There exist 4 exits and 4 entries. The first two (from the right, or east) have two general-purpose lanes metered separately, the third entry is fed by a slip ramp and a loop ramp (both metered separately), and all on-ramps contain HOV bypass lanes. This stretch of I-90 consistently contains 3 general-purpose lanes, but also contains an added left-side HOV lane that starts midway through the modeled site. The posted speed limit is 60 miles per hour (97 km/h), and the free flow speed generally ranges from around 60 to 75 miles per hour (97 to 121 km/h). Comparable occupancy rates for the I-90 model are found when modeled detectors are configured to be 13 by 6 feet (4.0 by 1.8 m).

4.4 DELAY ZONE CONFIGURATION

VISSIM contains functionality for measuring the travel time incurred by all vehicles that go from one location to another. Each of these zones is defined by two markers within the model's roadway network that signify the start and the end. Vehicles that travel within the zone but do not pass through both markers are not counted within that respected zone. These zones can also be used to measure delay. Delay in each vehicle is determined from the reduction of speed that effects some hindrance or obstruction. Examples of these include red signals, slow leading vehicles, and traffic congestion.

To understand the effect of each experimental scenario, delay zones positioned at all entry and exit points in the model have been divided into four classifications:

- **Controlled:** Traffic that has entered the freeway through a metered on-ramp. Note that the meter may not be operating per response group state at startup stages of each simulation run.
    - **1.** Traffic that passes through the incident site
    - **2.** Traffic that does not pass through the incident site. Note that some of this traffic may be affected by the congestion that results from the incident.
- **Uncontrolled:** Traffic that has entered on the mainline or through the unmetered express lane terminus (found in the I-5 model)
    - **3.** Traffic that passes through the incident site
    - **4.** Traffic that does not pass through the incident site.

VISSIM provides average delays representing all delay zones in each category. In our reporting, we consider Controlled categories together and both Uncontrolled categories together. The Controlled categories are an especially important indication of system performance because vehicles entering through metered entries are subject to ramp meter-induced delay on the on-ramps as well as incident-induced congestion on the mainline. These can then be compared with the Uncontrolled categories to understand the impact of the meters on traffic that is local to the incident site.

We also configured the following delay zones:

- **Entire network:** Controlled and Uncontrolled categories together. This is the overall network delay.
- **Incident area delay:** Delay zones positioned around the incident site and expected congestion growth area. This is an indication of congestion severity.
- **Ramp queue delay:** Each modeled ramp is equipped with a delay zone that measures signal-induced delay.
- **Spillover delay:** The model is configured with extra roadway beyond the entry of each on-ramp and corresponding delay zones to simulate surface streets. Any delay measured in these zones is an indication of queued traffic spilling out onto city streets. Severe cases imply a decrease in throughput. Spillover delay is reported separately from controlled traffic delay.
- **Secondary queuing delay:** Delay zones positioned in merging and weaving areas at the end of each on-ramp.

4.5 MODEL CONFIGURATION

4.5.1 VAP Structure

The VAP code for Fuzzy Logic and AIMD are unified into one code. This was partially done because of the shared code needed to facilitate the response group on/off mechanism for measuring Fuzzy Logic in a way equitable to AIMD in some of our tests.

This also allows for easier configuration for use with new models. Despite this code unification, the code is modular and can readily be broken apart into an AIMD-only implementation or a Fuzzy Logic-only implementation.

4.5.2 VAP Settings

Several variables introduced in the "methodology" section are defined as constants or defined when the system is informed of a new incident:

- **System-level variables:**
  - **Code timeslice:** The number of times per simulation cycle the VAP code is run: 2.
  - **Loop cycle:** The number of seconds each loop collects vehicle counts and occupancy between reads: 20 sec.
  - **Dwell time:** The minimum amount of time required for the demand detector to be occupied by a vehicle before the signal will turn green: 1.5 sec.
  - **Green time:** The time duration that the "green" signal head indicator is shown: 1.5 sec.
  - **Minimum red time:** The minimum duration that the "red" signal head indicator is shown: 1.6 sec. This plus the green time specify the minimum allowed cycle time. Note that since the VAP code is run twice each simulation second, the minimum red time is actually 2 sec. within our simulations. Our implementation maintains the residuals from this discrepancy and compensates throughout the run of the simulation.

- **Yellow time:** the amount of time ramp meters display the "amber" indication" before ramp metering begins: 3 sec. In VISSIM, this indication prompts virtual drivers to stop.
- **Maximum signal cycle:** The maximum cycle time allowed for the signal: 20 sec. This limits the AIMD maximum cycle to 0.7 sec. greater than the related Fuzzy Logic default setting.

- **Settings specific to AIMD:**
  - **Multiplier *m*** (see Section 3.2.4): This had been empirically found to work suitably at a setting of 0.33 in a series of initial tests.
  - **Response group strength β** (see Section 3.2.4): Most of our experiments had been run with this set at 1 (nominal strength). We have found, however, that minor adjustments between uncontrolled traffic efficiency and controlled traffic efficiency can be made by changing this parameter.
  - **Safely usable storage capacity *P*** (see Section 3.3): This generally ranges from 15 to 25 among all ramps.
  - **Ramp demand advance queue occupancy threshold** (see Section 3.3.5): 10%
  - **Ramp demand sampling cycles:** Ramp demand measurements are sampled over an extended period of time to produce a relevant, but stable value. We empirically chose 30, which represents 10 min.
  - **Excess demand coefficient** (see Section 3.3.4): 1.33
  - **Response group cycles:** This is the number of cycles that must occur between each reevaluation of response group size. Values too small are

sensitive to vehicle volume fluctuations, and values too high cause slow ramp meter response. We empirically chose 3 cycles which translates to 1 min.

  - **Response group queue threshold:** This estimated number of vehicles in the mainline queue must exceed this value in order for a response group to be established. We empirically chose 15. Values that were less caused the model to be susceptible to traffic volume fluctuations after the response group was empty, and values that were greater caused ramp meters to be shut off too soon.
  - **Decay factor** (see Section 4.5.3): Specific to each scenario.

- **Settings specific to Fuzzy Logic:**
  - All parameters and defaults for Fuzzy Logic come from the WSDOT Fuzzy Logic operations training material (Taylor and Meldrum, 2000a). We had communicated with knowledgeable personnel at WSDOT to receive updates in configuration information that had been a result of recent construction projects or adjustments due to changing travel patterns.

4.5.3 Vehicle Diffusion and Decay

In VISSIM, vehicles on modeled freeways sometimes totally stop in a mainline lane and wait for gaps in neighboring traffic to appear before making a lane change. This often happens at diverge points at exits and around incident sites. Ideally, these vehicles should have made the lane change further upstream. Although many vehicles do change lanes sufficiently early, not all vehicles follow suit.

Two scenarios happen in reality that cannot be modeled with existing simulation tools. First, VISSIM lacks the sufficient simulation of courtesy that many Seattle-area drivers give in letting such waiting drivers make desired lane changes. Second, in reality, if a driver cannot see an opening in a neighboring lane, the driver is conscious of the traffic that he or she is blocking in his or her own lane and drive onward to the next exit after a short period of time. By default, simulated drivers in VISSIM wait a default 60 seconds, creating an unrealistically sizeable traffic jam in the process.

We have not found a means to incorporate the first scenario into our model and do not believe that it is entirely necessary for sufficient quality in our results. But, the second scenario can be approximated by changing the VISSIM vehicle diffusion driver behavior parameter. We estimate that drivers will stand still on a roadway to make a lane change for an average of 5 seconds. In the simulation, if these vehicles cannot make the lane change, they are removed from the simulation. This produces a similar effect as drivers giving up on an intended lane change and instead accelerating.

Among our models, vehicles are removed from 0 to about 1.5 vehicles per simulated minute. For the higher rates of removals, this may result in over 30 vehicles disappearing from the traffic network. Unfortunately, no mechanism exists in VAP for detecting these removals. Therefore, there is no way to automatically account for these removals in the check-in/check-out mainline detector pairs that are used to estimate mainline queue length. This causes artificially high queue length estimations and can prevent the response group from becoming empty and shutting down.

The AIMD implementation is therefore equipped with a decay variable—a rate that is determined from one simulation run conducted for each scenario that adjusts the check-out counters to factor in the removed vehicles.

4.5.4 Fuzzy Logic Implementation

In order to facilitate an equitable comparison between AIMD and the algorithm in use by WSDOT, Fuzzy Logic, it was necessary to implement Fuzzy Logic to function as close to the actual WSDOT implementation as possible, as described in (Taylor and Meldrum, 2000a).

We note the following details that pertain to our implementation:

- WSDOT traffic operations personnel often manually turn on ramp meters upstream of congestion sites based upon intuition and experience. Ramp meters are often turned on in groups based upon proximity of ramps to the incident and proximity to other ramps. We consulted with one who had such experiences to verify that the Fuzzy Logic ramp meter selection was appropriate for the type and severity of incident being simulated (unpublished data). Generally, the meter (or group of meters) immediately upstream of the incident is enabled. Then, after approx. 5 minutes, if it is observed that the congestion caused by the incident is growing, the meter (or group of meters) upstream of the first activation are enabled. These activations remain in effect until it is observed that the congestion is cleared.
- The mechanism for triggering and resetting the ramp meter signal are different than the actual implementation. In our model, we do not use the passage detector

to verify that a vehicle has advanced. Since simulated VISSIM drivers always go on “green”, we assumed that this was of little concern.

- Each Fuzzy Logic meter is configured to observe the highest occupancy and speed from a specific selection of downstream mainline loop stations. In reality, many of these stations are beyond the end of the modeled area. We therefore do not observe the Fuzzy Logic algorithm responding to congestion that could happen far downstream of the incident location outside of our modeled area.
- The deployed implementation of Fuzzy Logic uses data from single loop detectors to derive local mainline speed—one of the inputs used by the algorithm in determining its output metering rate. This estimation is performed using this function (Taylor and Meldrum, 2000a):

$$Speed = \frac{Volume}{Occupancy \cdot g} \tag{25}$$

where

g is a constant factor to convert density to occupancy, as defined in (Taylor and Meldrum, 2000a).

Our models use the speed measurements provided by the virtual loop detectors, offering samples that are subject to far smaller variance.

- Differences in loop detector placements as described in Section 4.2 may affect overall performance of Fuzzy Logic. Since loop detectors are believed to be in comparable positions, it is assumed that the overall outcome is not significantly different. This is, however, a concern for future work when there are opportunities for revisiting simulated outcomes and comparing them with reality.

- For the two multi-lane on-ramps found in the I-90 model, the Fuzzy Logic implementation as coded approximates the implementation as specified by WSDOT (Taylor and Meldrum, 2000a). While the report calls for one Fuzzy Logic configuration per meter, we found it best to approximate the rates of each meter by treating the two-lane on-ramp as a whole and dividing the single rate by 2. For a more accurate Fuzzy Logic implementation, we can code all signals as being on separate ramps.

4.5.5 <u>Ramp Meter Shutdown Procedure</u>

As mentioned in Section 4.5.4, WSDOT traffic operations personnel today are responsible for manually enabling and disabling ramp metering within the Seattle area (unpublished data). After ramp metering is enabled, traffic operations personnel then monitor the freeway condition around the incident site to determine when it is appropriate to shut off ramp metering, such as when the incident is cleared. Traffic operations personnel may also elect to temporarily shut off meters for high-volume on-ramps in cases where mainline congestion is backing up onto a ramp and interfering with ramp meter operation.

In our simulations, we have automated the shutoff when we detect that no congestion exists. This detection is derived from the code pertaining to sectional check-in/check-out vehicle volumes that are used for AIMD response group establishment. This automation is designed to approximate traffic operations procedures, although we do acknowledge that this automated process likely shuts off meters sooner and reduces overall delay that would otherwise occur.

In current freeway operations, when ramp metering is shut off, the meters operate at the minimal cycle to quickly, yet gradually, empty the ramp queue to the freeway. The absence of such a scheme results in many vehicles being “dumped” onto the freeway at once—a likely source of additional congestion. When no vehicle presence is detected at the ramp meter for 4 seconds, the signal head is then shut off. This behavior is incorporated within our simulation models.

4.5.6 Accidents

The simulations conducted in this research sometimes do not show a significant difference between systemwide delays under the presence of ramp meter control versus delays under no ramp meter control. This is contrary to results seen in ramp meter studies such as the Minnesota shutdown (Cambridge Systematics, 2001) and the WSDOT Bottleneck study (Jacobson et al, 1989) that show dramatic improvements when ramp meter control is introduced to a region. A key factor for this discrepancy can be attributed to the fact that our simulation models do not incorporate the presence of accidents. Collisions within a merging area can dramatically affect vehicle flow and therefore cause congestion. The Minnesota and WSDOT studies show decreases in accident rates along with their observations of reductions in delay. Since all VISSIM modeled drivers are not capable of causing accidents, our models cannot address this important aspect of ramp metering.

4.6 TEST SCENARIOS

In order to evaluate AIMD’s performance under a variety of conditions, eight scenarios were created; the I-5 scenarios take place on Tuesday, August 8, 2006, and the I-90 scenarios are configured for Thursday, August 3, 2006. Vehicle volumes used are presented in Table 4-1 and Table 4-2. Note that the ramp numbers coincide with the segment numbers as seen in Figure 4-1 and Figure 4-2.

Table 4-1. I-5 vehicle volumes (veh/hr) on Aug. 8, 2006

Time	Main	On-ramps								Off-ramps					
		1	2	4	6	ExpLn.	9a	9b	12	2	3	4	7	9	10
8:00a	4631	439	432	289	777	0	158	428	596	299	544	380	793	269	513
11:00a	5372	616	424	281	628	0	212	492	622	444	661	485	1109	600	588
1:30p	4711	727	581	358	706	2077	281	601	739	506	684	567	1093	132	713

Table 4-2. I-90 vehicle volumes (veh/hr) on Aug. 3, 2006

Time	Main	On-ramps					Off-ramps			
		2	4	6a	6b	9	3	5	8	10
5:45a	2031	534	1210	686	588	492	205	145	158	607
9:30a	1820	587	1221	807	495	644	390	265	419	1191
4:00p	1755	427	889	711	433	928	305	365	354	869

In each of our scenarios, we simulate a congestion-causing incident that occurs 15 simulated minutes after the start. Delays are not recorded until 600 seconds. This allows for “warm-up time” within our simulation—a population of all regions of our model with a steady vehicle density. Each scenario is configured with the vehicle volumes for the main entry point, on-ramps, reversible express lane terminus (in the case of I-5 models), and off-ramps.

Each scenario generally involves a hypothetical accident blocking the right lane in a particular location. A driver in the area of the incident uses a cellular phone to report the general location of the incident to a traffic hotline. As a result, the regional traffic operations center personnel enables ramp metering on the freeway 2 minutes after the start of the incident in attempts to slow the growing congestion. (The actual average startup time reported by WSDOT for incident response notification is 1.75 minutes) (WSDOT, 2008). Meanwhile, an incident response crew is dispatched to mitigate the lane blockage. Our model unblocks the lanes after the respective duration, but the ramp meters are still enabled until a sufficient reduction in congestion is detected at the incident site.

Two variations of most scenarios involve the incident lasting 10 minutes and the incident lasting 20 minutes. We generally limit our cases to these durations because of current model implementation limitations in tracking the congestion area through multiple stations as identified in Section 3.2.3. We also note that among all types of incidents, the average incident duration is reported to be 14.0 minutes (WSDOT, 2008).

Each of our test scenarios are configured with 14% HOV vehicles. This had been found by comparing measured traffic volumes in HOV mainline and ramp bypass lanes with volumes found in general-purpose lanes during busy hours. Due to the possibility that some HOV vehicles may have occupied general-purpose lanes, this estimate is likely low.

We also estimated heavy vehicle proportions from length classifications collected by dual-loop detector stations. The proportion of heavy vehicles (or vehicles longer than 40 feet) was found to be approximately 6% of the total share during our simulation periods.

We set the duration of each simulation to encompass all incident-induced delay; each simulation generally ends when incident-induced delay is no longer present. For this reason, as well as the fact that our ramp meter algorithm implementation is limited in regards to properly handling recurring congestion, we chose times for simulations that involve moderate traffic—usually times that are at the start or end of a peak period. In our models, we found that congestion caused by lane-blocking incidents rarely cleared within peak periods.

4.6.1 I-5 Scenarios

Scenario 1a: 8:00 AM, after Lake City Way Interchange

This first scenario consists of an incident taking place in the 4th segment 650 ft (198 m) downstream of the Lake City Way on-ramp. This area of I-5 is curved, three lanes wide, and generally exhibits slower free-flowing traffic during this hour than seen in other portions of the model. This takes place during the reverse-morning commute time period. Three upstream on-ramps provide metered control.

Scenario 1b: 11:00 AM, after Lake City Way Interchange

Scenario 2 takes place at the same location as Scenario 1, but during a mid-day elevation in overall traffic volumes.

Scenario 2a: 8:00 AM, after Northgate On-Ramp

This third scenario takes place in the 9th segment 2100 ft (641 m) downstream of the Northgate on-ramp. This portion of roadway is five lanes wide due to the addition of two left-hand lanes at the terminus of reversible express lanes. Six upstream on-ramps are available within our model for controlling incoming traffic. Unlike all of the other scenarios, this scenario involves the blockage of three lanes. Three lanes are necessary for creating sufficient congestion at this time to warrant the use of ramp meters.

Scenario 2b: 1:30 PM, after Northgate On-Ramp

Scenario 2b's site is the same location as Scenario 2a's. This scenario involves the blockage of one right lane.

4.6.2 I-90 Scenarios

Scenario 3a: 5:45 AM, before 161st Ave. SE Off-Ramp

This scenario takes place at the beginning of the morning commute on Westbound I-90 in the 10th segment, 850 ft (259 m) upstream of the 161st Ave. SE off-ramp. This portion of I-90 is four lanes wide and rarely experiences recurring congestion.

Scenario 3b: 9:30 AM, before 161st Ave. SE Off-Ramp

Scenario 3b exists in the same location but at a later time. At 9:30 AM, the morning commute peak traffic conditions are coming to an end.

Scenario 4a: 9:30 AM, after W. Lk. Sammamish Pkwy. SE On-Ramp

We located the incident site within Scenario 4a to be 1000 ft (305 m) downstream of the W. Lk. Sammamish Pkwy. SE on-ramp, in the 9th segment. This is also a location that is free of recurring congestion.

Scenario 4b: 4:00 PM, after W. Lk. Sammamish Pkwy. SE On-Ramp

This final scenario takes place at the same location, but in the afternoon. As with the other I-90 scenarios, this time is normally free-flowing without recurring congestion. In order to illustrate the effects of incident-induced mainline queuing backing up into the W. Lk. Sammamish Pkwy. SE on-ramp on the AIMD and Fuzzy Logic ramp metering methods, a special 30-minute incident is simulated.

5 FINDINGS/DISCUSSION

5.1 I-5 SCENARIOS

Scenario 1a: 8:00 AM, after Lake City Way Interchange

Table 5-1 and Table 5-2 show the average vehicle delay (AVD), average number of stops, and vehicle counts amid our 10 simulation runs. Table 5-1 pertains to a lane-blocking incident that lasts for 10 minutes, while Table 5-2 pertains to a 20-minute incident. As described in Section 4.4, delay zones are configured within our model to report average delay on uncontrolled vehicles (e.g. those vehicles entering the roadway network through the freeway mainline), and controlled vehicles (e.g. those vehicles entering through on-ramps that are subject to metering).

Table 5-1. Scenario 1a results, 10 min.

Vehicles →	**Uncontrolled**			**Controlled**			**Ramps**	**Systemwide**		
↓ Algorithm	AVD*	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	27.7	0.2	2161	25.1	0.5	785	6.6	27.0	0.3	2946
Fuzzy Logic	30.7	0.3	2159	20.9	0.3	788	3.7	28.1	0.3	2946
No Control	32.0	0.4	2157	18.2	0.2	783	0.2	28.3	0.3	2940

* AVD = Average Vehicle Delay, in sec.

Table 5-2. Scenario 1a results, 20 min.

Vehicles →	**Uncontrolled**			**Controlled**			**Ramps**	**Systemwide**		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	71.7	1.2	3073	49.8	1.4	1118	14.1	65.9	1.3	4191
Fuzzy Logic	76.0	1.4	3070	44.4	1.1	1126	8.9	67.5	1.3	4195
No Control	81.3	1.6	3067	37.0	0.8	1121	0.7	69.4	1.4	4189

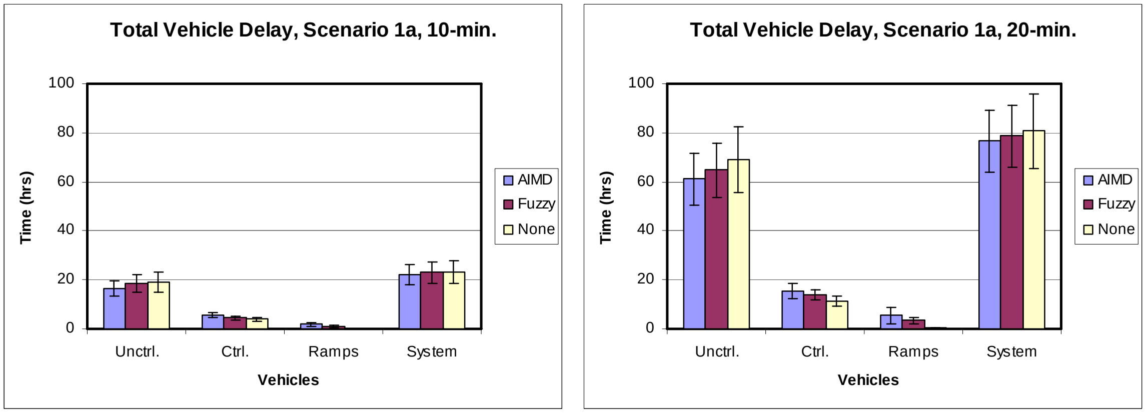


Figure 5-1. Scenario 1a total vehicle delay

Figure 5-1 shows the total vehicle delays for uncontrolled and controlled vehicles, as well as total systemwide delay. The error bars depict the 95% confidence interval of the mean for each category of total delay according to *t*-statistics. In order to illustrate the comprehensive effect of metering, the controlled delay includes traffic that is delayed on the ramps including overflows from ramp entrances. Average vehicle delay for this portion of controlled traffic is also reported separately. This is an important metric that can illustrate the potential negative impact of delay perceived by drivers desiring to enter the freeway. In reality, under severe delay, some of these vehicles may likely involve drivers that choose not to use the respective entrances and instead use surface streets to find other entrances to the freeway. We, however, are not able to reflect such drivers' route choice behaviors in our simulation experiments.

The 10- and 20-minute cases are configured to record delay for 32 and 45 simulation minutes, respectively, after a 10-minute warm-up period. 16% of the approx. 3460 veh/hr that pass through the incident site comes from ramps that can be metered.

This scenario shows a similar systemwide average vehicle delay of AIMD to that of Fuzzy Logic; p=0.16 for the 10-minute case and p=0.48 for the 20-minute case. But, there exists a significant difference in priorities between delays imposed on uncontrolled and controlled vehicles. AIMD decreases average delay on uncontrolled traffic from that of no control by 13.4% in the 10-minute case (p=0.01) and 11.8% in the 20-minute case (p=0.01). For the 10-minute case, AIMD performs significantly better than Fuzzy Logic, decreasing average uncontrolled delay by 9.8% (p=0.01); however, for the 20-minute case, AIMD's performance is comparable to that of Fuzzy Logic (p=0.21).

Scenario 1b: 11:00 AM, after Lake City Way Interchange

Table 5-3, Table 5-4, and Figure 5-2 show the results for this scenario. The 10-minute incident case records delay measurements for 35 simulation minutes, and the 20-minute case covers 60 minutes. Of the approx. 4350 veh/hr through the incident site, 15% originate from on-ramps that can be metered.

Table 5-3. Scenario 1b results, 10 min.

Vehicles →	**Uncontrolled**			**Controlled**			**Ramps**	**Systemwide**		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	50.4	0.5	2749	40.8	0.9	785	12.1	48.3	0.6	3535
Fuzzy Logic	54.8	0.7	2743	34.8	0.7	788	5.5	50.4	0.7	3531
No Control	56.1	0.8	2749	29.6	0.5	784	0.2	50.2	0.7	3533

Table 5-4. Scenario 1b results, 20 min.

Vehicles →	**Uncontrolled**			**Controlled**			**Ramps**	**Systemwide**		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	83.7	1.7	4694	53.9	1.6	1374	11.7	77.0	1.7	6067
Fuzzy Logic	83.1	1.6	4703	46.1	1.2	1376	6.1	74.7	1.5	6078
No Control	86.3	1.8	4702	40.3	0.9	1368	0.2	75.9	1.6	6069

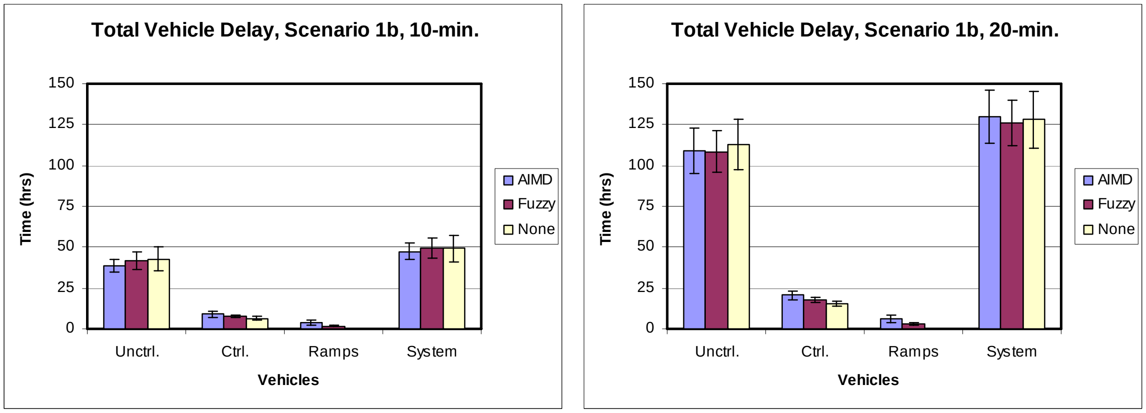


Figure 5-2. Scenario 1b total vehicle delay

Similar to Scenario 1a, comparable performance is again seen between AIMD and Fuzzy Logic for systemwide average delay in the 10-minute case (p=0.50) and the 20-minute case (p=0.39). For average vehicle delay among uncontrolled vehicles, the 8.0% reduction from the 10-minute Fuzzy Logic case to the AIMD case is still insignificant (p=0.28), and the slight increase from the 20-minute Fuzzy Logic case to the AIMD case is also insignificant (p=0.41).

Scenario 2a: 8:00 AM, after Northgate On-Ramp

Scenario 2a's results are shown in Table 5-5, Table 5-6, and in Figure 5-3. Delay measurements are recorded for 35 simulation minutes for the 10-minute case and 43 minutes for the 20-minute case. 47% of the approx. 4570 veh/hr through the incident site are potentially subject to ramp metering.

Table 5-5. Scenario 2a results, 10 min.

Vehicles →	Uncontrolled			Controlled			Ramps	Systemwide		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	30.6	0.5	2780	39.4	0.9	1736	15.4	33.9	0.7	4156
Fuzzy Logic	35.7	0.7	2773	32.8	0.7	1737	0.8	35.5	0.7	4155
No Control	34.8	0.7	2777	31.6	0.6	1740	0.3	34.4	0.7	4159

Table 5-6. Scenario 2a results, 20 min.

Vehicles →	Uncontrolled			Controlled			Ramps	Systemwide		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	66.9	1.9	3698	87.9	2.4	2344	30.6	75.0	2.1	5555
Fuzzy Logic	76.5	2.3	3704	74.9	2.3	2349	7.6	77.9	2.4	5562
No Control	79.6	2.4	3693	73.0	2.2	2350	0.2	79.3	2.4	5562

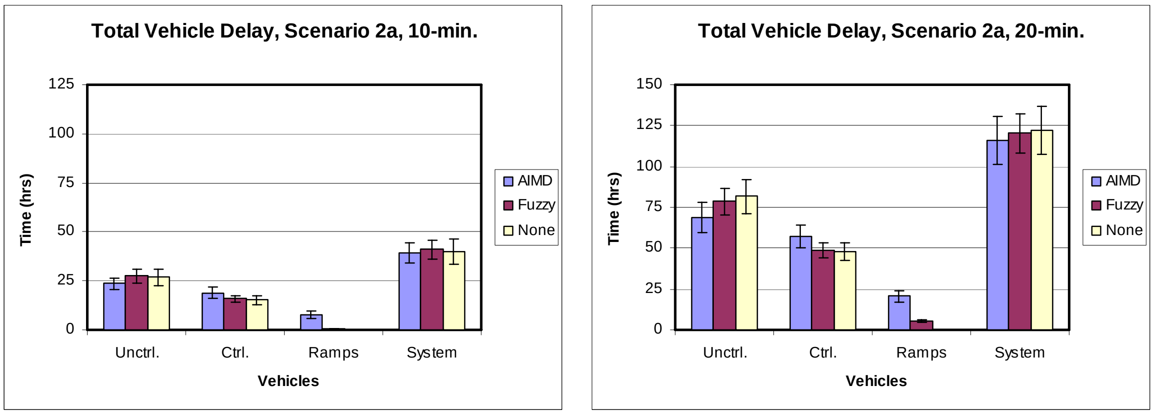


Figure 5-3. Scenario 2a total vehicle delay

While AIMD does not offer significantly different systemwide average delay than no control in the 10-minute case (p=0.73), it does offer a significant 5.4% delay reduction from no control in the 20-minute case (p=0.04). The systemwide average delay for Fuzzy Logic, on the other hand, is not significantly different than that of no ramp meter control in both cases (p=0.38 and p=0.67 for 10- and 20-minute cases, respectively). For the 10-minute case, a significant 14.2% reduction in average vehicle delay for uncontrolled vehicles is seen from that of Fuzzy Logic (p=0). The corresponding 20-minute case provides a 12.5% reduction in average delay (p=0.01).

Scenario 2b: 1:30 PM, after Northgate On-Ramp

Table 5-7, Table 5-8, and Figure 5-4 show the results for Scenario 2b. In this scenario, 67 simulated minutes of delay are recorded for the 10-minute case, and 140 minutes are recorded for the 20-minute case. Of the approx. 6740 veh/hr that pass through the incident site, 40% come from on-ramps that are subject to metering.

Table 5-7. Scenario 2b results, 10 min.

Vehicles →	Uncontrolled			Controlled			Ramps	Systemwide		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	39.5	0.2	7576	46.3	0.5	3921	5.2	42.8	0.3	10577
Fuzzy Logic	43.2	0.2	7563	47.3	0.5	3921	1.3	46.0	0.3	10557
No Control	44.5	0.2	7583	47.8	0.5	3918	0.3	47.0	0.3	10576

Table 5-8. Scenario 2b results, 20 min.

Vehicles →	Uncontrolled			Controlled			Ramps	Systemwide		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	59.2	0.3	15920	68.8	0.8	8261	5.1	64.3	0.5	22251
Fuzzy Logic	63.2	0.4	15936	71.9	0.9	8272	3.7	68.2	0.6	22272
No Control	70.5	0.5	15920	76.1	1.0	8257	1.3	74.8	0.6	22248

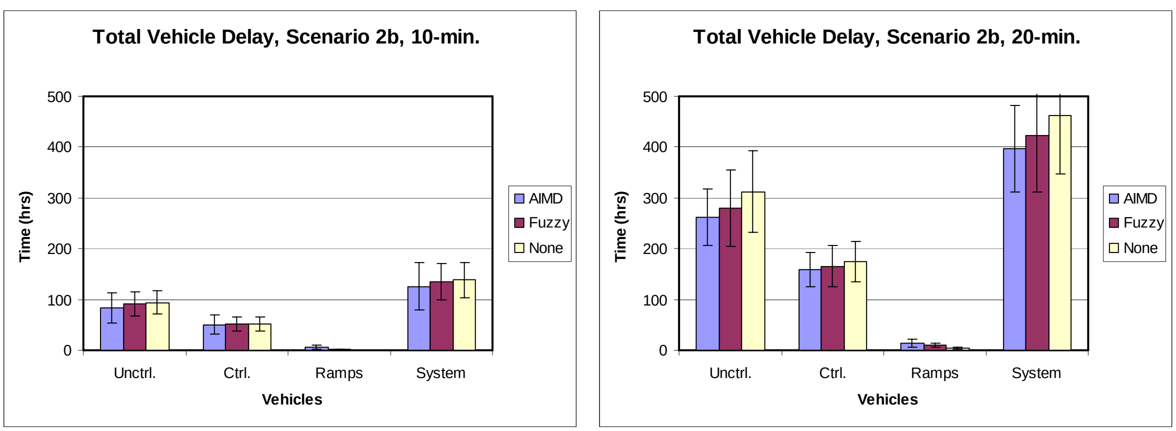


Figure 5-4. Scenario 2b total vehicle delay

Here, both Fuzzy Logic and AIMD reduce systemwide delay from the None case. Fuzzy Logic's systemwide reduction in average vehicle delay is varied (p=0.39 and p=0.05 for the 10- and 20-minute cases, respectively), and AIMD's benefits follow suit (p=0.09 and p=0.04 when compared with no control for 10- and 20-minute cases, respectively). Here, however, a moderate difference is seen in the average delay reduction for uncontrolled traffic between AIMD and no control; where Fuzzy Logic offers varied reductions in delay (by 2.9% and 10.4% for 10- and 20-minute cases, respectively; p=0.36 and p=0.03), AIMD offers more significant reductions by 11.2% and 16.0% for the 10- and 20-minute cases, respectively (p=0.04 and p=0.03).

5.2 I-90 SCENARIOS

Scenario 3a: 5:45 AM, before 161st Ave. SE Off-Ramp

The results for Scenario 3a are found in Table 5-9, Table 5-10, and Figure 5-5. The 10-minute incident simulation recorded delay for 52 simulation minutes and the 20-minute incident simulation recorded delay for 82 simulation minutes. Of the approx. 3930 veh/hr passing through the incident site, 66% originate from on-ramps.

Table 5-9. Scenario 3a results, 10 min.

Vehicles →	**Uncontrolled**			**Controlled**			**Ramps**	**Systemwide**		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	73.6	0.9	1752	97.6	1.5	3015	16.4	88.7	1.3	4767
Fuzzy Logic	111.5	2.1	1749	130.4	2.7	2996	9.8	123.5	2.5	4745
No Control	114.8	2.1	1751	125.0	2.4	2995	0.8	121.2	2.3	4746

Table 5-10. Scenario 3a results, 20 min.

Vehicles →	**Uncontrolled**			**Controlled**			**Ramps**	**Systemwide**		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	175.0	3.7	2756	204.6	4.8	4685	17.0	193.7	4.4	7442
Fuzzy Logic	202.0	4.7	2756	221.5	5.5	4679	12.1	214.3	5.2	7435
No Control	208.3	5.0	2752	217.6	5.5	4666	0.8	214.2	5.3	7418

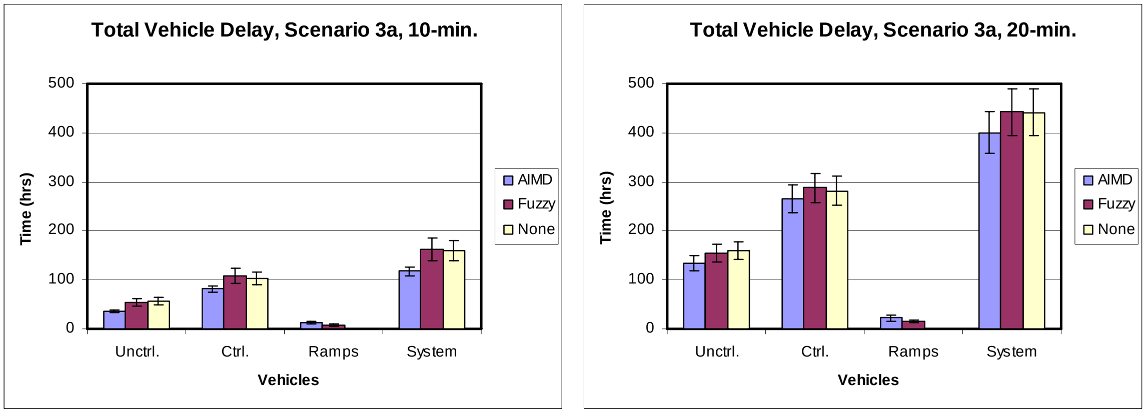


Figure 5-5. Scenario 3a total vehicle delay

Fuzzy Logic offers no significant systemwide difference in average delay when compared with no control ($p=0.58$ and $p=0.99$ for 10- and 20-minute incident durations, respectively). However, this scenario shows a marked benefit in systemwide average delay for AIMD when compared with Fuzzy Logic—decreases by 28.2% and 9.6% for 10- and 20-minute cases, respectively ($p=0$ and $p=0.03$).

Note in particular how the average vehicle delay is reduced on the controlled vehicles between AIMD and Fuzzy Logic by 25.1% and 7.6% for 10- and 20-minute cases, respectively ($p=0.00$ and $p=0.06$). We discuss possible causes for these results in the next section.

Scenario 3b: 9:30 AM, before 161st Ave. SE Off-Ramp

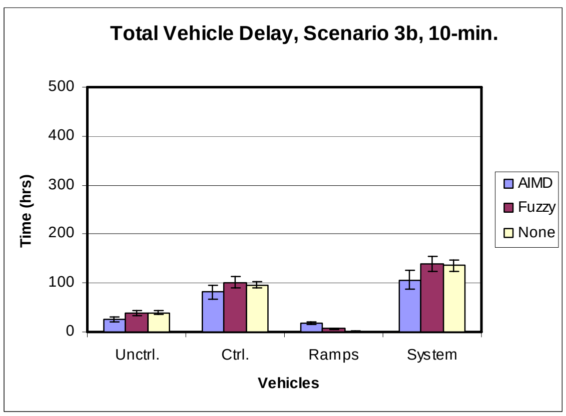
Table 5-11, Table 5-12, and Figure 5-6 show the results for Scenario 3b. For the 52 simulation minutes of recorded delay in the 10-minute case and the 73 minutes of recorded delay in the 20-minute case, 73% of the approx. 3310 veh/hr that reach the incident site come from controllable on-ramps.

Table 5-11. Scenario 3b results, 10 min.

Vehicles →	Uncontrolled			Controlled			Ramps	Systemwide		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	58.7	0.9	1571	91.0	1.9	3214	19.8	80.4	1.6	4786
Fuzzy Logic	88.5	2.0	1570	114.2	2.8	3199	7.3	105.7	2.5	4768
No Control	90.3	2.1	1571	108.9	2.7	3194	1.0	102.8	2.5	4764

Table 5-12. Scenario 3b results, 20 min.

Vehicles →	Uncontrolled			Controlled			Ramps	Systemwide		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	169.1	4.5	2233	231.3	6.7	4472	29.2	210.6	6.0	6704
Fuzzy Logic	201.4	5.8	2230	254.5	8.0	4452	22.8	236.8	7.3	6682
No Control	222.8	6.6	2224	260.7	8.0	4423	1.5	248.0	7.5	6646



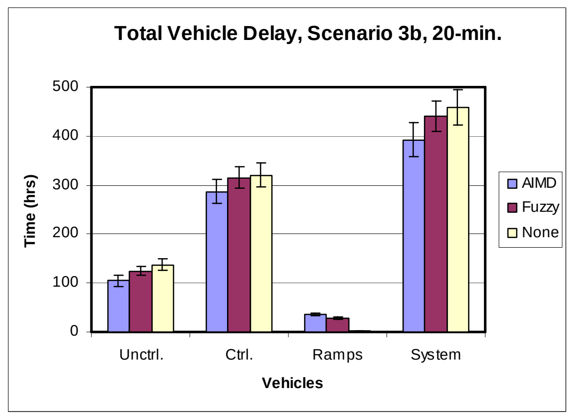


Figure 5-6. Scenario 3b total vehicle delay

The behavior of this scenario is similar to that of Scenario 3a. Again, the difference in average systemwide delay between Fuzzy Logic and no control is insignificant (p=0.50 and p=0.24). AIMD offers significant systemwide reduction in average delay from that of Fuzzy Logic—a 23.9% reduction in the 10-minute case and an 11.1% reduction in the 20-minute case (p=0.00 for both).

Scenario 4a: 9:30 AM, after W. Lk. Sammamish Pkwy. SE On-Ramp

Table 5-13, Table 5-14, and Figure 5-7 show the results for Scenario 4a. Vehicle delays are recorded for 37 simulation minutes in the 10-minute case and 57 minutes in the 20-minute case. Of the approx. 3500 veh/hr that pass through the incident site, 73% are subject to the possibility of ramp meter control.

Table 5-13. Scenario 4a results, 10 min.

Vehicles →	Uncontrolled			Controlled			Ramps	Systemwide		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	26.7	0.2	1116	41.2	0.5	2310	11.4	36.5	0.4	3426
Fuzzy Logic	34.3	0.3	1115	42.9	0.5	2311	4.5	40.1	0.4	3426
No Control	36.1	0.4	1116	40.4	0.5	2306	0.7	39.0	0.5	3422

Table 5-14. Scenario 4a results, 20 min.

Vehicles →	Uncontrolled			Controlled			Ramps	Systemwide		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	48.5	0.6	1727	73.4	1.4	3543	19.9	65.2	1.1	5270
Fuzzy Logic	60.3	0.9	1726	78.9	1.5	3545	13.0	72.7	1.3	5271
No Control	82.6	1.6	1726	90.1	1.8	3541	0.8	87.6	1.7	5267

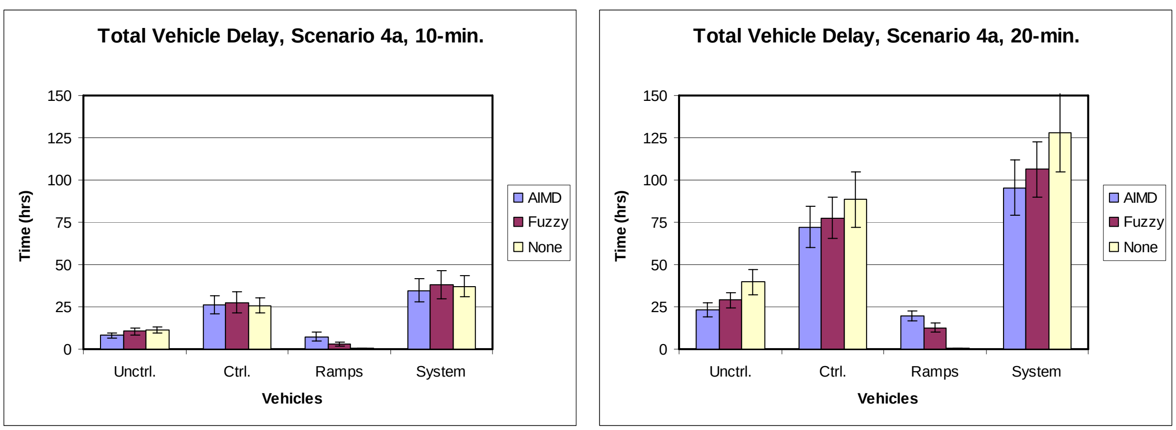


Figure 5-7. Scenario 4a total vehicle delay

In the 10-minute case, the systemwide average vehicle delay between no control and Fuzzy Logic is not significantly different (p=0.73). The corresponding 9.0% reduction from Fuzzy Logic to AIMD is moderately significant, however (p=0.08). But, in the 20-minute case, Fuzzy Logic significantly reduces the systemwide average vehicle delay by 17.0% (p=0.03). The additional 10.3% reduction from Fuzzy Logic afforded by AIMD in this 20-minute case is moderately significant (p=0.08). As in previous scenarios, the delay imposed by ramp metering on controlled vehicles for the 20-minute case results in complete systemwide improvement that reduces the overall average delay of all classifications of vehicles.

Scenario 4b: 4:00 PM, after W. Lk. Sammamish Pkwy. SE On-Ramp

In this final scenario, results are shown in Table 5-15, Table 5-16, and Figure 5-8. The 10-minute case had been configured to record delay for 28 simulation minutes and the 20-minute case recorded delay for 45 simulation minutes. The traffic volume through the incident site was approx. 2540 veh/hr, including 74% from on-ramps.

Table 5-15. Scenario 4b results, 10 min.

Vehicles →	**Uncontrolled**			**Controlled**			**Ramps**	**Systemwide**		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	23.5	0.2	831	48.4	1.0	1592	20.3	39.9	0.7	2423
Fuzzy Logic	30.8	0.4	829	49.5	1.0	1593	7.2	43.1	0.8	2422
No Control	34.1	0.5	829	49.7	1.0	1596	4.2	44.4	0.8	2425

Table 5-16. Scenario 4b results, 20 min.

Vehicles →	**Uncontrolled**			**Controlled**			**Ramps**	**Systemwide**		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	34.6	0.5	1329	83.3	2.1	2531	36.9	66.5	1.5	3860
Fuzzy Logic	49.8	1.0	1330	83.1	2.1	2528	18.0	71.6	1.8	3858
No Control	54.2	1.2	1329	80.8	2.1	2526	11.1	71.6	1.8	3856

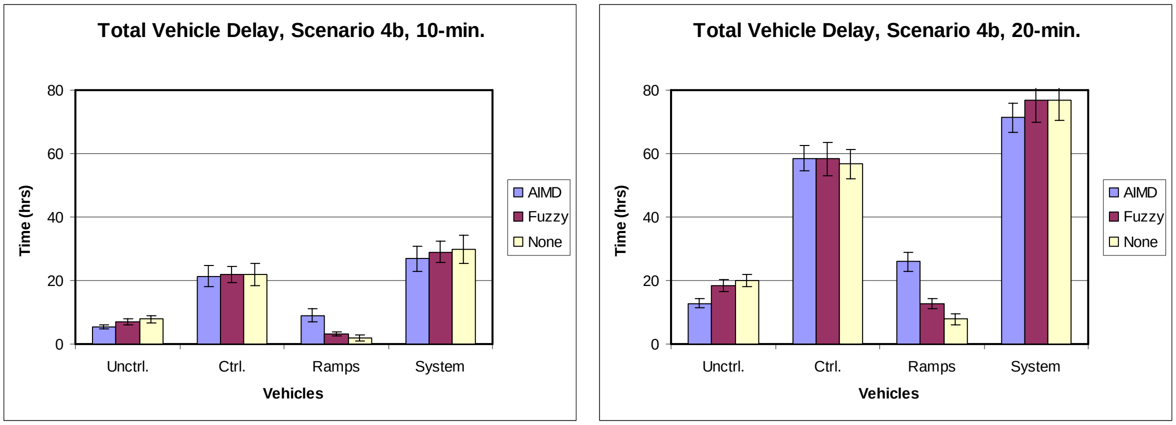


Figure 5-8. Scenario 4b total vehicle delay

Fuzzy Logic exerts comparable average systemwide delay as the None case in both 10- and 20-minute cases (p=0.48 and p=0.99, respectively). This scenario shows a moderately reduced average systemwide delay for AIMD from that of Fuzzy Logic in the 10-minute case—a decrease by 7.4% (p=0.06). For the 20-minute case, AIMD's reduction by 7.1% is significant (p=0.02).

This general trend is also seen in the average vehicle delays for uncontrolled traffic. While Fuzzy Logic does show a significant reduction in delay from no control by 9.7% and 8.1% for 10- and 20-minute cases, respectively (p=0.01 and p=0.03), AIMD shows a further significant reduction from that of Fuzzy Logic by 23.7% and 30.5% (p=0.01 and p=0.03).

In this scenario, we observe traffic that backs up into the W. Lk. Sammamish Pkwy. SE on-ramp and overflows when the incident is allowed to last for long periods of time. To compare the response of AIMD to that of Fuzzy Logic under this overflow condition, we conducted another case for this scenario—a 30-minute incident. The results for this case are shown in Table 5-17 and Figure 5-9.

Table 5-17. Scenario 4b results, 30 min.

Vehicles →	Uncontrolled			Controlled			Ramps	Systemwide		
↓ Algorithm	AVD	Stops	Count	AVD	Stops	Count	AVD	AVD	Stops	Count
AIMD	54.5	1.1	1765	121.9	3.3	3358	45.3	98.7	2.6	5123
Fuzzy Logic	70.4	1.8	1763	122.3	3.5	3362	28.6	104.4	2.9	5125
No Control	76.3	2.0	1763	119.9	3.5	3356	24.7	104.9	3.0	5119

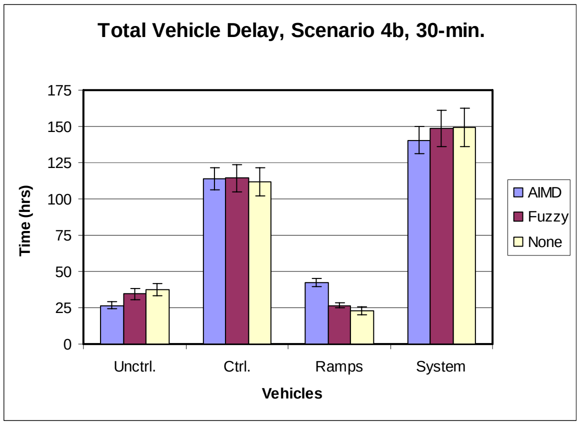


Figure 5-9. Scenario 4b total vehicle delay for 30-minute incident

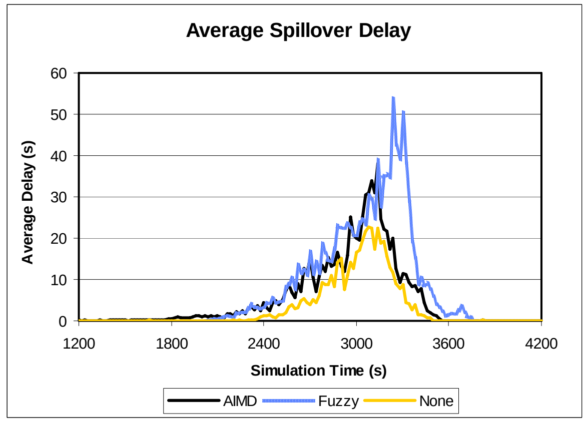


Figure 5-10. Spillover delay on the I-90 Segment 9 on-ramp

Here, the systemwide average vehicle delay of Fuzzy Logic is not significantly different than no control (p=0.89), but the uncontrolled average vehicle delay for Fuzzy Logic is significantly less than that of no control by 7.7% (p=0.03). AIMD shows a significant reduction in systemwide average vehicle delay from Fuzzy Logic by 5.4% (p=0.02), and also a corresponding reduction in uncontrolled vehicle average delay by 22.6% (p=0).

As the incident remains in effect, the queue forming behind the incident site on the mainline backs up into the on-ramp and eventually overflows beyond the end of the ramp. As seen in Figure 5-10, all three ramp metering cases show the occurrence of spillover, indicated by vehicle delay measured within the spillover region of the modeled on-ramp. Fuzzy Logic shows a significant amount of added delay. We have observed that the rule structure of Fuzzy Logic aggravates the spillover condition; while traffic is backed up into the on-ramp, the traffic queue also overlaps the local mainline loop detectors. This causes a high occupancy reading to be made for the local occupancy input for the Fuzzy Logic method. Although rules are also in place for accelerating the ramp meter rate at times of high queue and advance queue detector occupancy, this does not result in metering rates that lead to similar spillover behavior as seen under AIMD and no meter control. It is at such times that traffic operations personnel may elect to manually switch off the Fuzzy Logic metering in order to reduce such spillover (unpublished data). Given AIMD's similarity in spillover delay to the no ramp metering case, such a manual shutoff is not as necessary for AIMD.

5.3 <u>DISCUSSION</u>

A characteristic of several scenarios such as Scenario 1a is the apparent lack of differences in delays between the presence of ramp meter control and no ramp meter control. When comparing systemwide delay under Fuzzy Logic to no ramp meter control in Scenario 1a, a paired *t*-test shows insignificant differences (p=0.79 for the 10-minute case and p=0.38 for the 20-minute case). As described in Section 4.5.6, the benefits of ramp metering regarding the reduction of accident rates within merging areas is not testable using our models; therefore, this important benefit is not considered in the comparisons of average and total delays between metered and unmetered cases. This is a likely contributing factor to the prevalence of insignificant differences in delays among ramp meter methods.

Another contributing factor to Fuzzy Logic's insignificant change within our experiments may be inherent in its sensor placements and its corresponding ramp metering rate response. In the times of day chosen for our simulations that feature free-flowing traffic under normal circumstances, most areas within the models continue to contain free-flowing traffic when the incident is underway. Queues behind incidents grow considerably—sometimes to thousands of feet over several minutes—before they reach local loop detectors. Until high occupancy readings are registered at local loop detectors, Fuzzy Logic operates at a fast metering rate and causes practically no vehicles to be withheld from the mainstream. Its only significant benefit can therefore be prevalent in the merging area—especially if accident rates are incorporated into our tests. AIMD, on the other hand, begins the metering rate at the ramp upstream of the incident at a third of the demand rate and adjusts its rate until the entire ramp capacity is utilized, adding additional ramps as necessary—a response specifically intended to reduce mainline queue severity.

As hinted in the sometimes wide spread of the error bars in the total delay graphs, delay results can vary considerably among the 10 runs that comprise a complete simulation for a particular scenario, ramp meter method, and incident duration. While we occasionally encountered unusually sizeable outliers in our data and subsequently changed the range of random number seeds for the 10 runs to avoid them, we found that some series of runs still offered high variance. We attributed outliers to the few times we observed erroneous behavior in the simulations, such as deadlocked vehicles. Even so, in the 20-minute case of Scenario 1b for example, measurements for average system delay ranged from 63.7 sec. to 142.1 sec. We have yet to determine whether this spread is an issue that pertains to the intended operation of the simulation software. Until this is clarified, all results with these kinds of spreads, including the favorable I-90 scenarios, must be regarded with this in mind.

The percentage of vehicles encountering an incident site that come from controlled on-ramps likely dramatically affects the success of our ramp meter experiments. This vehicle mixture affects the amount of control that a ramp metering method can exert on freeway congestion. In particular, it is helpful to observe that the I-5 scenarios feature a mixture with a low percentage of controlled vehicles, whereas the I-90 scenarios exhibit a higher percentage. Our modeled section of I-90 also incorporates ramps with larger storage capacities than found on our I-5 model.

Another factor that can influence ramp meter simulation results is the overall vehicle volume, affected by time of day. We believe that there exist ranges of optimal volumes and vehicle mixtures that allow for uncommonly favorable ramp meter performance in the models. As described in Section 6.2, it has yet to be determined through future research how broad these peak-performance ranges are, and whether there exist ways for capitalizing on various system characteristics of these time periods.

6 CONCLUSIONS

6.1 SUMMARY

Inspired by computer network control theory, we have devised a preliminary strategy for ramp metering that attempts to provide a strong, immediate response to congestion caused by freeway incidents. The AIMD mechanism is also intended to minimize the chances for vehicles queued in on-ramps to spill out into local streets. Our simulation scenarios—involving a 5.6 mile (9.0 km) model of Interstate 5 in Seattle and a 6.7 mile 10.8 km) model of Interstate 90 with free-flowing traffic—compare the performance of AIMD and Fuzzy Logic strategies, as well as no ramp metering.

We observed from our 8 simulations scenarios that our new method exhibits a systemwide performance that is comparable or better than Fuzzy Logic. In particular, AIMD significantly reduces the average systemwide delay by as much as 28.2% from that of Fuzzy Logic. In one scenario, AIMD reduces ramp spillover into surface streets that was otherwise observed with Fuzzy Logic. In this scenario, systemwide average delay is reduced by 5.4% from that of Fuzzy Logic.

While it is possible for this strategy to be invoked automatically, we infer that it may be actively initiated as a traffic control mechanism by traffic operations personnel as incidents are discovered or reported. Since our work is not optimal for all congestion scenarios, we also anticipate that this strategy can supplement or be integrated with other ramp meter strategies, enabling the best performance for a wide variety of circumstances.

6.2 RECOMMENDATIONS

The authors recommend that further study be conducted on the AIMD algorithm and its use in traffic operations. These recommendations are necessary to leverage the findings within this research to fully realize the method's potential for directly influencing congestion.

A key factor in the comparison of ramp meter algorithm effectiveness is the accuracy of traffic models under congested conditions. Overall, a ramp metering algorithm provides systemwide benefit if the delay imposed upon vehicles within the ramp is less severe than the consequential delay imposed by those vehicles within the mainline queue at the incident site. Although the simulated models have been calibrated under free-flowing conditions, this research has not incorporated a comprehensive evaluation of accuracy under congested conditions. Model inaccuracies can consequently cause the severity of mainline vehicle congestion to be misestimated, resulting in systemwide delay measurements that do not show full advantage for ramp metering methodologies such as Fuzzy Logic or AIMD. In this research, the level of simulated congestion severity has been found to be sensitive to simulator version number, mechanisms used to impose congestion, the number of simulation cycles per second, and driver behavior parameters used at the site of the incident. From observation, overall vehicle dissipation in some cases is believed to be too rapid, reducing the perceived systemwide benefit of ramp metering. Further research is therefore needed in ensuring realistic operation for congested conditions; this may necessitate repeated on-site investigation of nonrecurring congestion cases as well as the use of multiple simulation software packages.

Many of our simulation scenarios did not show significant delay reductions between the presence of ramp metering control and no control. This can largely be attributed to the lack of accidents within our model as described in Section 4.5.6, as well as calibration challenges as described in the previous paragraph. We have observed, however, that overall demand depending upon the time of day play a significant role in ramp meter effectiveness; ramp metering is ineffective in our models when traffic is too sparse or too congested. Further study should be given to the effectiveness of ramp metering in context of varying systemwide volumes. This can assist in determining appropriate responses to incidents given the time of day, incident type, and location.

Our models' adherence to today's roadway sensor configurations limit AIMD's theoretical potential for congestion prevention. The AIMD method is intended to reduce mainline traffic buildup immediately, but when it is enabled well after congestion has begun, its utility can be diminished. Since we had always assumed a two-minute startup time in our scenarios and also assumed the use of discrete loop detectors that only allow for a view of systemwide traffic conditions at sparsely-spaced points within the corridor, we have found that our capabilities of addressing the incident properly are limited. To evaluate the benefit of advanced incident detection technologies as identified in Section 3.5.2 (e.g. denser sensor networks, or zone-wide vehicle detection rather than point-based), AIMD can readily be configured to take advantage of such technologies in ways that are not as apparent with Fuzzy Logic. Valuable insight would be gained from determining whether this would result in significant congestion reduction.

Various improvements can be made to the AIMD implementation, including improved techniques for demand rate tracking (see Section 3.3.2), congestion detection (Section 3.5.2) and end-of-incident shockwave tracking (Section 3.5.3).

Our simulation scenarios only pertain to incidents that occur during times of free-flowing traffic. While we only report simulations of nonrecurring congestion, we do anticipate that it is possible to represent choke points within AIMD similar to incidents. This is another aspect that should be studied further.

The scenarios in this work consist of hypothetical incidents. To better evaluate the performance of AIMD, a simulation scenario should consist of an incident that had actually occurred and had created enough disturbances to be clearly identifiable within the archived traffic volume data. A simulation of the same kind of incident can then allow better determination of the accuracies of the model in terms of reduced capacity vehicle flow, ramp metering rates, and congestion duration.

The current implementation of AIMD assumes accurate vehicle counts between check-in and check-out detectors on on-ramps as well as the mainline. Work similar to that performed for SZM by Liu et al (2007) in evaluating improved, robust methodologies for vehicle counting should be applied to this research. Techniques may include using occupancy to estimate density and using filtering algorithms to increase the accuracy of vehicle counts. In considering loop detectors, it has been observed that occupancy is a better measure for detecting ramp queue presence than volume counting (Taylor and Meldrum, 2000b). Reasons for this include detector misalignment to vehicles' paths of travel as well as lane-changing and weaving patterns that cause multiple counts or no counts. Ultimately, this potentially high signal-to-noise ratio can produce bad aggregations.

The traffic volume data used in our research had been retrieved from TDAD (Traffic Data Acquisition and Distribution) system (Dailey and Pond, 2001), an online data retrieval application developed by the University of Washington College of Engineering Intelligent Transportation Systems Research Program. Although it would have been preferable for recently archived traffic detector measurements to be used, this 20-second data source is no longer available. 20-second data, as opposed to 5-minute or 1-minute data, is necessary for research projects such for many reasons. For example, the variance found in 20-second data is helpful for understanding various traffic patterns as well as diagnosing the presence of inaccurate loop detectors. We therefore find it critical to have access to timely 20-second data for quality traffic operations research.

Factoring street traffic volumes feeding the on-ramps is another important consideration for further research. The proper modeling of signalized intersections that are near the entrances of on-ramps allows for realistic patterns of vehicles to be directed to on-ramps. This platooning, or grouping of vehicles, may impact the overall performance of ramp metering and show additional benefit in terms of reduced secondary queuing in the merge area.

Finally, we believe that that the evaluation of any ramp metering algorithm within a test region of a freeway corridor can offer more concrete conclusions than simulation alone. A study can evaluate the overall delay imposed upon controlled and uncontrolled vehicles before and after the introduction of the new algorithm. Although VISSIM simulates vehicles in a microscopic fashion, its car following model bears some insufficiencies for traffic traveling at low speeds in freeway congestion as described earlier. Additional possible differences in simulated traffic behavior as compared with observed traffic behavior include merging aggressiveness, lane-changing behavior upstream of a diverge point, accident rate (for all simulated drivers are perfect drivers), and the courtesy that some drivers offer to others who are making a lane change, as described in Section 4.5.3. While AIMD requires more development before on-site testing is appropriate, all simulation results should be evaluated with this possibility in mind.

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