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ABSTRACT

A capacity analysis approach intended as an alternative to the traditional Highway Capacity Manual (HCM) method was evaluated. One- and two-stage models of pre-queue and queue discharge flow (each of which might be thought of as representing “capacity” in some sense) were developed and compared with one another and the HCM method. Two-stage models related capacity flows to intervening variables, including average time gaps (average time separations between the rear of a vehicle and the front of one following it) in the critical lane (that with the highest flow rate) and the critical lane flow ratio (the flow in the critical lane divided by the average flow per lane), and then related these intervening variables to the geometric, vehicle population, and driver population characteristics of bottleneck sites. One-stage models involved direct relationships between capacity flows and site characteristics. Differences in capacity flow among study sites were primarily the result of differences in average critical lane time gaps; however, critical lane flow ratios were also important. The performance of the one-stage and two-stage models was similar. For the sites used to develop the models, both were better able to predict pre-queue and queue discharge flows than was the HCM method. In particular, the HCM method tended to overestimate actual bottleneck flows, especially in queue discharge. However, neither type of model was successful in explaining variations in capacity flows at additional sites used for verification. Once apparently anomalous data were eliminated, the only significant explanatory variable in the models was the number of lanes. Consequently, it is recommended bottleneck capacity analyses continue to be based on existing HCM methods but that these be supplemented by use of a look-up table based on the means and standard deviations of pre-queue and queue discharge flows for sites with particular numbers of lanes.

Keywords: traffic capacity analysis, bottleneck capacity

EXECUTIVE SUMMARY

This report documents results of a research project entitled "New Approach to Bottleneck Capacity Analysis." This project evaluated a capacity analysis approach that was intended as an alternative to the traditional Highway capacity (HCM) method. The project developed and compared one- and two-stage models of pre-queue and queue discharge flow with one another and the HCM method. Two-stage models related capacity flows to a set of intervening variables that included the average time gaps in the critical lane (that with the highest flow rate) and the distribution of flow across the lanes, represented by the critical lane flow ratio (the flow in the critical lane divided by the average flow per lane) and then related the intervening variables to the geometric, vehicle population, and driver population characteristics of bottleneck sites. One-stage models involved direct relationships between capacity flows and site characteristics.

The alternative approach to capacity analysis begins with the observation that flow is the reciprocal of the average headway and that the headway, which is the time separation between common points on successive vehicles (for instance, front bumper to front bumper), may be decomposed into the passage time (the time it takes the vehicle to pass a point) and the time gap between the rear of the lead vehicle and the front of the following one. Consequently, the maximum flow in the critical lane at a bottleneck is a function of the average values of the time gaps and the passage times in capacity flow, and the average flow per lane is a function of the critical lane flow and the critical lane flow ratio. The overall relationship is

$$\bar{q} = \frac{\alpha}{r_c\left(\bar{g}_c + \bar{p}_c\right)}$$

where $\bar{q}$ = arithmetic mean flow per lane
$\bar{g}_c$ = average time gap in the critical lane
$\bar{p}_c$ = average passage time in the critical lane
r_c = critical lane flow ratio
α = ratio of arithmetic mean flow to harmonic mean flow

Since past research indicated that critical lane flow ratios and average time gaps in the critical lane vary widely among bottleneck sites, it was hoped that they would prove to be stable and predictable features of the sites, and that this would allow more accurate predictions of bottleneck capacity. In particular, it was hoped that the new approach would result in better understanding of variations in capacity at different bottlenecks.

As originally proposed, the study was to have involved analysis of data from at least 20 freeway bottlenecks. Initially, 25 potential sites in the San Diego, Seattle, and Minneapolis-St. Paul metropolitan areas were identified. As a result of various problems with the availability and quality of the automatically-collected data, several of these had to be eliminated outright. In addition, most of the sites in San Diego did not have detectors located directly in the bottleneck sections. It had originally been hoped that the

average time gaps in the critical lanes would be similar at the bottleneck and at locations immediately upstream, so that these sites could still be used in the development of the models. When this proved not to be the case, these sites had to be eliminated from the set used to develop the models, although they were used for verification of the models. A set of 15 sites was used in initial development of the models; one of these was subsequently eliminated because the data appeared to be anomalous, so that 14 sites were used in the development of the final version of the capacity models.

For each of the sites, traffic data were collected for a total of about 60 weekdays during the summer of 2004. In addition, a smaller set of data from the Minneapolis-St. Paul area was available; these data were collected in 2000 during an experiment in the in which ramp meters were turned off. These data were screened to eliminate obviously corrupt data, days with rainfall, days with known incidents, and time periods with obviously anomalous flow.

It is well established that the highest-volume uncongested flows occurring immediately before flow breakdown are typically higher than the queue discharge rate following breakdown, and that such pre-queue flows can sometimes last for considerable periods of time. There is continuing debate among researchers about whether bottleneck capacity should be defined as queue discharge flow, pre-queue flow, or some combination of the two. The approach followed in this study was to consider both pre-queue flow (PQF) and queue discharge flow (QDF) as representing "capacity" in some sense, and to attempt to model both conditions.

An initial step in data reduction was to identify periods of PQF and QDF. QDF was taken to begin at flow breakdown, as indicated by an abrupt decrease in speed upstream from the bottleneck, and to end when speeds recovered. PQF was defined as any period of near-constant flow ending in local flow breakdown. Abrupt decreases and increases in speed were identified from re-scaled plots of cumulative speed, and periods of near-constant flow were identified from re-scaled cumulative flow plots. Once flow periods were identified, means and standard deviations the various flow characteristics were calculated for each period. These were subsequently aggregated over all episodes of PQF and QDF at each site to produce means and standard deviations of the flow characteristics for each site.

Analysis of variance was used to test whether there were significant differences in the mean values of the flow characteristics during different episodes of PQF and QDF at each site and *t*-tests were used to verify that differences in flow were significant. The results suggested that PQF and QDF are indeed distinct flow conditions, but that they may not be homogeneous – that is, the characteristics of the periods identified as PQF or QDF are not necessarily the same every time they occur. Analysis of variance was also used to verify that there were significant differences in the means of the flow characteristics at the different sites. The analysis of the flow characteristics for the individual sites also suggested that QDF varies by time of day, at least for sites where congestion extends outside the traditional commute trip periods.

Relationships among flow characteristics at different sites were investigated by preparing scatter plots and calculating correlation coefficients. As a result of this analysis, it was concluded that capacity flows are most strongly influenced by average time gaps, but that lane flow distributions are also important. Further, the analysis suggested that there is a strong, near-linear relationship between flow and average time gaps in the critical lane (although the linearity is contrary to what would be expected from the a priori relationship among flow, passage time, and time gap). Since the relationship appeared to be linear, least-squares regression analysis was used to determine lines of best fit for the PQF and QDF cases.

Following the evaluation of the relationships among the flow characteristics, one- and two-stage models of PQF and QDF were developed and evaluated. Two-stage models employed a relationship between capacity flow and the intervening variables of the following form

$$q = \frac{a - bg}{r_c}$$

where q = capacity flow (PQF or QDF), g = average critical lane time gap, and r_c = critical lane flow ratio, with a and b determined by the linear regression described above and g and r_c related to the site characteristics by separate multivariate regression models. One-stage models were multivariate regression models that related capacity flows to site characteristics directly.

Data related to site characteristics included lane configurations, vertical alignment, vehicle classification data, and census data (used to estimate driver population characteristics). To estimate driver population characteristics, census tracts believed to represent reasonable commuter-shed zones were identified; socioeconomic characteristics of the drivers were assumed to be similar to those of the general population in these zones. Specific site-related data used in the development of the models included the number of lanes; the grade approaching the site; the percentage of heavy vehicles in the traffic stream; the on-ramp and off-ramp flows upstream and downstream of the bottleneck, the HCM heavy vehicle factor; and the median age, median income, percentage of males aged 18 to 24 years, percentage of college graduates, and population density of the commuter shed zones.

Stepwise regression was used to isolate the variables having the greatest influence on the various flow characteristics. These were identified as (*a*) the median income of the commuter-shed zone and percentage of males aged 18 to 24 years in the case of flow per lane (i. e., the one-stage model) and average critical lane time gaps and (*b*) the percentage of males aged 18 to 24 years and the percentage of college graduates in the case of the critical lane flow ratio. Multivariate regression models incorporating these variables were then calibrated. In addition, models were calibrated in which the critical lane flow ratio at merge and diverge bottlenecks was related to the ratios of on- and off-ramp flow to mainline flow. This resulted in a set of six models – a one-stage model and two two-stage models each for PQF and QDF.

These models were evaluated by comparing their performance with one another and with the bottleneck capacities estimated by the HCM method. These comparisons were carried out for both the sites used for calibration and the six additional "verification sites" in San Diego. The result was that the one-stage and two-stage models performed very similarly: at the sites used to develop the models, they were nearly unbiased and explained a significant amount of the variability in PQF and QDF, but at the verification sites, although they displayed relatively small biases, they did not explain the variability of capacity flows. Meanwhile, the HCM methods seriously overestimated both PQF and QDF (except in the case of PQF at the verification sites) and in all cases failed to explain the variation in flow.

Inspection of the flow and census data used to calibrate the models suggested that they might have been unduly influenced by data from one Minneapolis site that appeared to have anomalous characteristics (very high percentage of males aged 18 to 24 years and very low PQF and QDF). When data from this site were omitted, the stepwise regression analysis indicated that the only significant explanatory variable was the number of lanes. Since this model could not explain the variation in capacity flow at the verification sites (all but one of which have four directional lanes) it was concluded that none of the models provides a satisfactory explanation of the variation in PQF and QDF among sites.

On the basis of these results, it is recommended that bottleneck capacity analyses continue to be carried out with existing HCM methods but that these be supplemented by comparing them with the look-up table below that gives, for freeways with different numbers of directional lanes, (*a*) the approximate range of PQF and QDF between one standard deviation below and one standard deviation above the mean and (*b*) the approximate range of the standard deviations of the mean flows for different episodes of PQF and QDF. This table may be used to identify possible biases in the results of HCM analyses, to provide for separate estimates of PQF and QDF, and to quantify the uncertainty of capacity estimates.

Recommended Ranges for Pre-Queue and Queue Discharge Flow Estimates

Number of directional lanes	Flow range, veh/h/lane		Standard deviation of mean flows for individual episodes, veh/h/lane	
	PQF	QDF	PQF	QDF
2	2015 – 2120	1820 – 1995	90 – 150	50 – 105
3	2045 – 2150	1945 – 2035	75 – 110	50 – 90
4	2050 – 2365	1915 – 2165	70 – 170	35 – 80

It is also recommended that (*a*) the table be refined by increasing the sample of bottlenecks used to develop it, (*b*) automatic techniques for identifying PQF and QDF periods by developed, (*c*) Caltrans consider upgrading the freeway traffic surveillance system and providing for better maintenance of it, (*d*) Caltrans pursue collection of data

on the socioeconomic characteristics of specific traffic streams (i. e., for specific sites and time of day), and (*e*) that Caltrans conduct intensive studies of bottleneck performance as an alternative to the sort of extensive study described here.

TABLE OF CONTENTS

Page

Page

TABLES AND FIGURES

Page

Page

Page

1. INTRODUCTION

This report documents the development and evaluation of a new approach to capacity analysis for freeway bottlenecks. The proposed approach was intended as an alternative to the methods in the current Highway Capacity Manual (HCM) (Transportation Research Board, 2000). This alternative approach involved transformation of commonly-available traffic data to provide greater insight into driver behavior. Transformed traffic characteristics included average passage times (the time it takes the vehicle to pass a point) and time gaps (between the rear of the lead vehicle and the front of the following one) in the critical lane (the lane with the highest traffic volume) and the ratio of the critical lane flow to the flow per lane. The overall approach of the study was to use these transformed characteristics as intervening variables to link capacity flows to the geometric, vehicle population, and driver population characteristics of bottlenecks. This two-stage process was intended to provide greater insight into the factors influencing bottleneck capacity and improved estimates of the capacity of freeway bottlenecks in urban and suburban areas.

1.1 Freeway Bottleneck Performance

Bottlenecks are the critical points in freeway networks and are consequently the major source of recurrent congestion. Almost all efforts to mitigate freeway congestion, whether they involve the planning and design of physical improvements or traffic management initiatives, require assessment the capacity of existing or potential bottlenecks and understanding of how capacity is affected by particular design features and management strategies.

Past research related to freeway bottleneck capacity includes discussions of the concept of capacity, observations of maximum flow rates under various conditions, and detailed studies of the functioning of bottlenecks. This research forms the basis for the 2000 edition of the HCM, which is the standard reference on the subject. Issues which have not yet been fully resolved include (*a*) the definition of capacity, (*b*) the extent to which capacity varies over time for individual bottlenecks, (*c*) the extent of and reasons for variations in capacity among different bottlenecks, and (*d*) the behavioral basis of bottleneck capacity.

Empirical studies related to the functioning of bottlenecks are fundamental to both the concept of capacity and the specific flow rates believed to represent capacity. One topic of particular concern has been the transition from uncongested to congested flow (Banks 1990, 1991; Hall 1991; Urbanik 1991; Ringert 1993; Elefteriadou 1995, 2003; Cassidy 1999; Persaud 1998, 2001; Zhang 2004a, 2004b, Rudjanakanoknad 2005). Most studies have found a decrease in flow in the lane that experienced the heaviest flow prior to the transition, and flow across all lanes has also been found to decrease in many cases, but not always. The existence of cases in which flow across all lanes has decreased in the transition to congestion has led to the question of whether capacity should be regarded as the maximum uncongested flow rate experienced prior to flow breakdown or the queue discharge flow rate that follows breakdown. The most common conclusion appears to be that capacity should be defined in terms of queue discharge flow (Hall 1991); however, both flow rates may be important for some traffic management purposes. Elefteriadou (2003) noted a decrease in flow immediately prior to breakdown, and suggested that at least three different flow rates be considered, Zhang (2004a) proposed that capacity be defined as a weighted average of pre-queue and queue discharge flows, and Lorenz (2001) proposed a probabilistic definition. Meanwhile, values of capacity for basic freeway segments cited in the current edition of the HCM are derived primarily from Schoen (1995) and are based on the highest 15-minute flows observed at their study sites. This value, although most likely to represent pre-queue flow, may be greater than sustained flow rates over longer periods for either pre-queue or queue discharge flow.

Specific flow rates believed to represent capacity have evolved over time. Prior to the late 1980s the commonly accepted capacity for basic freeway sections under ideal conditions was 2000 passenger cars/hour/lane (pc/h/ln). A number of studies in the late 1980s and early 1990s indicated that this value was too low for many locations (Persaud 1988; Banks 1989, 1991; Urbanik 1991; Chin 1991). The treatment of basic freeway segment capacity in the current HCM is based primarily on Schoen et al (1995), and consists of a relationship in which ideal capacities for urban commute traffic vary from 2250 to 2400 pc/h/ln based on free-flow speed. Schoen states, however, that the data suggested that capacity did not vary for free-flow speeds greater than 60 mph (100 km/h); the scheme incorporated in the HCM was adopted primarily because of its compatibility with material elsewhere in the manual. The treatment of weaving section capacity in the HCM is derived primarily from Reilly (1984) and defines capacity in terms of density. The treatment of ramp and ramp junction capacity is based for the most part on Roess and Ulerio (1993). In this case, capacities are usually the same as those of the basic freeway segments upstream of off-ramps or downstream from on-ramps. In addition to these studies, there are a number that have examined the effect of incidents and environmental conditions on freeway capacity (Hall 1988, Ibrahim 1994, Jones 1970, Goolsby 1971, Dudek 1982, Dudash 1983, Van Goeverden 1998).

Other issues related to bottleneck capacity include the stability of queue discharge and the time required to transition from uncongested flow to stable queue discharge. Studies examining these issues include Cassidy (1999), Zhang (2004a), Urbanik (1991), Persaud (1998, 2001), and Lorenz (2001).

1.2 Current Highway Capacity Manual Methods

The methods in the current HCM apply to three types of bottlenecks: basic freeway segments (HCM Chapter 23), weaving sections (HCM Chapter 24), and ramps and ramp junctions (HCM Chapter 25). In practice, however, the capacity calculations for basic freeway segments and ramps and ramp junctions are the same. The Manual assumes that the capacity-limiting section at a ramp junction may be the ramp itself, the intersection at the terminal of a diamond exit ramp, or the freeway segment immediately upstream of an off-ramp or immediately downstream of an on-ramp, but not the merge or diverge itself. Consequently, in most cases the limiting capacity at a ramp junction will actually be that of a mainline freeway segment. Note that bottlenecks are often attributed to merges, but it is the effect of the merge on the demand flow for the section immediately downstream that is assumed to be the key to creating the bottleneck, not the effect of the merge maneuver on the capacity of the freeway. The capacity of on-line weaving sections may be limited by the capacities of the entrance or exit legs, but is also represented as being affected by the length of the weaving section and the proportion of the flow in the section that weaves.

As previously stated, the HCM assumes that capacity for basic freeway segments varies with free-flow speed. This involves the further assumptions that the speed-flow relationship is influenced by the free-flow speed over the entire range of flow and that capacity occurs at the same density (28 passenger cars/lane/km or 45 passenger cars/lane/mi) regardless of free-flow speed. The resulting capacity is given by

$$c = 1{,}800 + 5FFS \tag{1}$$

where FFS = free flow speed
c = capacity

The HCM states that free-flow speeds should be measured in the field wherever possible, but also gives a relationship for calculating default values for free-flow speed. This relationship is

$$FFS = BFFS - f_{LW} - f_{LC} - f_N - f_{ID} \tag{2}$$

Where $BFFS$ = base free flow speed 110 km/h or 70 mph (urban) or 120 km/h or 75 mph (rural)
f_{LW} = adjustment for lane width
f_{LC} = adjustment for right-shoulder clearance
f_N = adjustment for number of lanes (urban freeways only)
f_{ID} = adjustment for interchange density

Thus the HCM implies that free flow speed (and, indirectly, capacity) is dependent on lane width, right shoulder clearance, interchange density, and (in the case of urban freeways) the number of lanes. Meanwhile, the capacity flow rates are stated in terms of 15-minute flow rates and apply to passenger cars operated by “regular and familiar” users of the facility. Hourly volumes across all lanes are converted to adjusted peak 15-minute flow rates in passenger cars per hour by means of

$$v_p = \frac{V}{(PHF)(N)(f_{HV})(f_p)} \tag{3}$$

where v_p = 15-minute passenger car equivalent flow rate
V = hourly volume
PHF = peak hour factor
N = number of lanes
f_{HV} = heavy-vehicle adjustment factor

f_p = driver population factor

The heavy vehicle factor and the driver population factor can have a major impact on the adjusted flow rate; hence, the HCM implies that these are among the most important factors influencing capacity. The heavy vehicle factor depends on the proportions of two types of heavy vehicles (trucks and buses, considered as a single type, and recreational vehicles) and the length and steepness of grades. This factor is calculated as

$$f_{HV} = \frac{1}{1 + P_T\left(E_T - 1\right) + P_R\left(E_R - 1\right)} \tag{4}$$

where E_T,E_R = passenger car equivalents for trucks/buses and recreational vehicles in the traffic stream

P_T,P_R = proportion of trucks/buses and recreational vehicles in the traffic stream

The passenger car equivalents in turn, depend on the length and steepness of the grade and the proportion of heavy vehicles in the traffic stream. The overall relationship is complicated and was derived primarily by microscopic modeling rather than extensive analysis of empirical data. It assumes that the influence of heavy vehicles is the result of both their greater size and their tendency to travel at low speeds on upgrades and severe downgrades. As heavy vehicle speeds decrease on long, steep grades, other vehicles are assumed to switch out of the lanes they occupy. This leads to underutilization of the lanes occupied by the heavy vehicles and concentration of passenger cars in the other lanes. The passenger car equivalent of a single heavy vehicle is least where the proportion of heavy vehicles is low because the impact on the utilization of the lane is proportionally greater. (That is, the heavy vehicles remain in the lane but the passenger cars switch lanes; thus the fewer heavy vehicles there are, the fewer vehicles use the affected lane or lanes and the greater the impact on the adjusted flow rate.)

The HCM provides little guidance on the selection of driver population factors. It states that the traffic stream characteristics that are the basis of its methodology apply to "regular drivers in a substantially commuter traffic stream, or in a stream in which most drivers are familiar with the facility" and that traffic streams with different characteristics may use freeways less efficiently and thus have lower capacities. It further states that significantly lower capacities have been observed on weekends, particularly in recreational areas. The adjustment factor is allowed to take on values between 0.75 and 1.00, with 1.00 representing commuter traffic or regular users, but the exact value is left up to the analyst, and no further guidance is given.

The HCM method for weaving segments defines capacity in terms of traffic density. For freeway weaving sections, the limiting density is stated to be 27 passenger cars/lane/km or 40 passenger cars/lane/mi. Note that these densities are somewhat less than those for basic freeway segments. The Manual justifies this practice on the grounds that "due to the additional turbulence in weaving segments, it is believed that breakdown occurs at somewhat lower densities than for basic freeway…segments." Traffic density in the weaving section, in turn, is calculated by dividing the total flow in the weaving section by the average speed in the section. The overall average speed is taken to be a weighted average of the speeds of weaving and non-weaving vehicles, and these speeds, in turn, are calculated by

$$S_i = S_{\min} + \frac{S_{\max} - S_{\min}}{1 + W_i} \tag{5}$$

where S_i = average speed of weaving or non-weaving traffic
$S_{\min}$ = minimum speed expected in the weaving segment
$S_{\max}$ = maximum speed expected in the weaving section
W_{i} = weaving intensity factor

Finally, the weaving intensity factor (for analysis using metric units) is given by

$$W_i = \frac{a(1 + VR)^b (v/N)^c}{(3.28L)^d} \tag{6}$$

where VR = volume ratio – that is, ratio of the weaving flow to the total flow
v = total flow rate in the weaving segment
N = number of lanes in the weaving segment
L = length of the weaving segment in meters
a,b,c,d = constants of calibration

The total flow v is given in passenger cars/hr and is adjusted for the peak hour factor, the heavy vehicle factor and the driver population factor. The constants a, b, c, and d depend on the type of weaving segment, whether weaving or non-weaving traffic is being considered, and whether the weaving segment is "constrained" – that is, whether the weaving vehicles can occupy as many lanes as they need to achieve equilibrium operation. Note that, since the weaving influence factor depends on such features as the type of weaving section, its length, and the volume ratio, this method implies that the capacity of weaving segments depends on these features as well as the factors affecting basic freeway segment capacity. It should also be noted that this method is somewhat controversial and sometimes produces unsatisfactory results (Cassidy 1989).

The HCM-2000 method for ramps and ramp junctions assumes that conditions in the vicinity of merge or diverge may be important in determining the level of service, but that they do not affect the capacity. The manual states that "research has shown that the turbulence due to merging and diverging maneuvers does not affect the capacity of the roadways involved, although there may be local changes in lane distribution and use." Consequently, except in cases where the ramps themselves or off-ramp terminals are the limiting factor, the methods for determining the capacity of ramp junctions are the same as those for basic freeway segments. It should be noted, however, that there is evidence to the contrary – that is, that the mechanics of the merge maneuver and the loading in individual lanes can indeed affect flow rates though the sections immediately downstream from on-ramps (Elefteriadou 1995).

Key features of the HCM approach that apply to all the freeway elements considered may be summarized as follows: (*a*) capacity is defined as the maximum 15-minute flow rate; (*b*) capacity is assumed to occur at some critical density, and hence to vary with the free flow speed and other features of the speed-flow relationship; however, there is no clear concept of how or why free flow speed affects capacity; (*c*) the capacity of facilities used by urban commute traffic is assumed to vary with vertical alignment and heavy vehicle presence, but not with driver population characteristics; even where driver population characteristics are assumed to be important, it is not known what characteristics are important, why they are important, or exactly how much effect they have.

This approach to capacity analysis suffers from several limitations. First, the definition of capacity is ambiguous and may not be appropriate. Periods of high-volume pre-queue flow (PQF) and periods of queue discharge flow (QDF) may each last more than 15 minutes and either may be said to represent "capacity" in some sense. In defining capacity as the maximum 15 minute flow, the HCM obscures the issue of whether PQF or QDF is meant. Depending on the situation, either flow rate may be of importance: however, in most cases what is really important is either the average flow rate that can be sustained for an entire period of PQF or QDF (however long it lasts) or, in the case of PQF, the relationship (if any) between the average flow rate and the amount of time it can be sustained before flow breaks down. In either case, it may also be important to know the variability of average flow rates for different flow periods. Another limitation of the HCM method is that it provides little insight into how driver behavior affects capacity. Finally (and perhaps most importantly), it seems unlikely that differences in free-flow speed and the effects of heavy vehicles can explain the full range of PQF and QDF observed at urban and suburban sites during commute peaks. Most such sites are relatively flat, have fairly low proportions of heavy vehicles during peak periods, and have reasonably similar free-flow speeds. Yet Schoen (1995) reported that queue discharge rates ranged from 1,700 to 2,350 passenger cars/lane/h and, as will be shown subsequently, the range of "capacities" found in this study is on the order of 25 percent the mean under both pre-queue and queue discharge conditions.

1.3 Proposed Alternative Approach

An alternative to the HCM approach is to treat PQF and QDF separately, to analyze these flows in terms of flow characteristics that appear to reflect fundamental aspects of driver behavior, and then use these characteristics as intervening variables to link the vehicle population, driver population, and geometric characteristics of bottlenecks to their PQF and QDF.

Note that flow is the reciprocal of the average headway, and that the headway, which is the time separation between common points on successive vehicles (for instance, front bumper to front bumper), may be decomposed into the passage time (that is the time it takes the vehicle to pass a point) and the time gap between the rear of the lead vehicle and the front of the following one. Thus the capacity of an individual lane is a function of speed, average vehicle size, and of some critical average time gap. The mathematical relationships are given by

$$q_i = \frac{1}{\overline{h}_i} \tag{7}$$

where q_i = flow in lane i
$\overline{h}_i$ = average headway in lane i

and

$$\overline{h}_i = \overline{g}_i + \overline{p}_i \tag{8}$$

where $\overline{g}_i$ = average time gap in lane i
$\overline{p}_i$ = average passage time in lane i

Consequently,

$$q_i = \frac{1}{\overline{g}_i + \overline{p}_i} \tag{9}$$

Note that where flows and headways are averaged over many count intervals, the flow in Equation 7 will actually be the harmonic mean flow. Because the arithmetic mean flow is normally of more interest in capacity analysis, it is necessary to take the relationship between the arithmetic mean and the harmonic mean into account. For cases in which averages over many count intervals are under consideration, Equation 7 may be modified to

$$\overline{q}_{hi} = \frac{1}{\overline{h}_i} \tag{7a}$$

where $\overline{q}_{hi}$ is the harmonic mean flow. The relationship between the harmonic mean and the arithmetic mean flow may be stated as

$$\overline{q}_i = \alpha \overline{q}_{hi} \tag{10}$$

where $\overline{q}_i$ is the arithmetic mean flow for lane i and α is the ratio of arithmetic mean to harmonic mean; α is always greater than 1.0 but will vary depending on the distribution of the headways in the lane.

From this perspective, the capacity of an individual lane at a bottleneck will depend on the speed in the bottleneck (which may not vary a great deal, especially in QDF) and the average time gap, which depends on the collective behavior of the drivers. Past research by Banks (2003) indicates that although individual time gaps vary widely, and for reasons that are by no means fully understood, average time gaps in congested flow at any given site display very little variation with speed over the range of 20 – 80 km/h. On the other hand, average gaps do vary by as much as 50 percent at different sites and/or times of day. Consequently, the capacity of individual bottleneck lanes may be primarily the result of a feature of the collective behavior of drivers in a particular traffic stream that is relatively stable under congested conditions.

Meanwhile, capacity is usually thought of as being the flow per lane averaged across all the lanes of the bottleneck section. Consequently, the overall capacity of a bottleneck may be a function of both the capacity of some individually critical lane and the distribution of flow across all lanes. That is

$$\bar{q} = \frac{\alpha}{r_c\left(\bar{g}_c + \bar{p}_c\right)} \tag{11}$$

where the subscript c refers to the critical lane and

$$r_c = \frac{q_c}{\bar{q}} \tag{12}$$

where

r_c = critical lane flow ratio
q_c = critical lane flow
$\bar{q}$ = average flow per lane

Consequently, bottleneck capacity depends on the critical lane average time gap (hereafter referred to as simply the “gap”), the critical lane average passage time (referred to as the “passage time”) and the critical lane flow ratio (CLFR).

In uncongested flow, lane flow distributions appear to be largely a result of a combination of driver behavior and the configuration of the facility. For instance, it has been hypothesized that individual drivers choose particular lanes because of a desire (or lack thereof) to go fast (Daganzo, 2002a, 2002b). At the same time, however, the presence of entrances and exits will affect lane use in their immediate vicinity. In heavily congested flow upstream of a bottleneck, flow rates in individual lanes (and hence the lane flow distribution) may be controlled by conditions downstream, but in the bottleneck itself they should be primarily the result of local driver behavior. Past research indicates that this behavior is affected by the transition from uncongested to congested flow (Banks, 1991; Ringert, 1993). Finally, Amin (2003) has shown that the CLFR varies by as much as 40 percent at different sites in congested flow in the vicinity of bottlenecks, which suggests that CLFRs (like gaps) are site-specific.

The evidence of wide variation among sites in CLFRs and gaps in critical lanes and the evident dependence of lane flow distributions and gaps on fundamental features of driver behavior suggests that capacity analysis using these features as intervening variables might improve insight into how driver behavior affects capacity. In addition, it may prove easier to explain lane volume distributions and gaps in terms of site, vehicle, and driver characteristics than to explain variations in capacity directly. If so, this approach could lead to a better understanding of bottleneck capacity and more accurate capacity predictions.

A number of characteristics of drivers, vehicles, and freeway facilities might be responsible for the variation among sites in gaps and lane flow distributions. Gaps may depend on the aggressiveness and attentiveness of drivers, and on acceleration and deceleration characteristics that are a function of both the vehicle and the roadway. In this case, driver aggressiveness refers to the willingness to maintain small gaps under ideal conditions; attentiveness refers to both the drivers' motivation to pay close attention to maintaining their spacing and to the presence or absence of distractions. Driver aggressiveness may depend on socioeconomic characteristics such as age, gender, income, or place of residence (urban, suburban, or rural; also possibly the size of the metropolitan area); trip purpose; sight distance; and the driver's confidence in the vehicle's deceleration capability. The usual assumptions regarding the influence of these characteristics on aggressiveness are that aggressiveness increases with wealth (because of higher time values and better vehicles), decreases with age, is greater for males than females, increases with metropolitan area size and population density (because of the "faster pace of life"), and is greatest for work trips. Driver attentiveness may depend on age, trip purpose, time of day (independent of trip purpose – people may be less alert in the evening than in the morning, for instance), and the overall complexity of the traffic situation. In addition to the effect of deceleration capabilities on driver aggressiveness, acceleration characteristics may affect gaps by affecting the drivers' ability to quickly close excessive gaps. Acceleration and deceleration, in turn, are affected by the power/weight ratio of the vehicle, the quality of its braking system, and the roadway grade.

Lane flow distributions may be affected by driver aggressiveness (in the sense of both the motivation to drive fast and the willingness to maintain close spacing); roadway grade and vehicle population characteristics; and lane configurations, including the locations of entrances and exits, weaving sections, and lane drops. As in the case of gaps, driver aggressiveness may be related to socioeconomic characteristics and trip purpose. It is reasonable to suppose that the effect of vehicular characteristics and roadway grades will be similar to that implied by the HCM method: that is, where there are heavy vehicles on upgrades or steep downgrades, faster vehicles will exit the lanes occupied by the heavy vehicles, and this will result in a higher CLFR. Also, as in the HCM method, the maximum impact is expected to occur with relatively low proportions of heavy vehicles. Finally, the presence of entrances and exits (especially heavily-used exits) is expected to reduce CLFR, and in some cases to shift the critical lane (in terms of flow) from the inside lane to the outside lane. This is expected to apply to both normal ramp junctions and weaving sections.

The considerations just discussed form the basis for a set of hypotheses about how the physical, driver population, and vehicle population characteristics of different bottleneck sites should affect their gaps and CLFRs. It may not be possible to test all of these hypotheses, but taken together, they provide a starting point for the explanation of variations in flow characteristics.

- Gaps will be related negatively to the proportions of young people, males, and wealthy people in the traffic stream.
- CLFR will be related positively to the proportions of young people, males, and wealthy people in the driver population.
- From the two preceding hypotheses, CLFR and gaps will be negatively correlated.
- Gaps will be related negatively to metropolitan area population and the population density in the vicinity of the site.
- CLFR will be related positively to metropolitan area population and population density in the vicinity of the site.
- Gaps will be smaller during work trip peaks than at other times of day.
- Gaps will be larger where there are complicated traffic situations (weaving, high levels of lane changing, closely-spaced ramps, left hand entrances or exits, etc.) than where traffic situations are simple.
- Gaps will be related positively to roadway grade, especially in QDF.
- CLFR will be related positively to the proportion of heavy vehicles and the length and steepness of grade.
- CLFR in critical sections will be related negatively to the ratios of entering and exiting flow to overall flow.

2. METHODOLOGY

There are two general approaches to the study of traffic behavior at freeway bottlenecks. One, that might be termed the *intensive* approach, involves detailed study of individual bottlenecks to determine (*a*) when, where, and how flow breaks down; (*b*) how the bottleneck functions thereafter; and (*c*) whether flow through the bottleneck can be increased or flow quality in the vicinity of the bottleneck improved and, if so, how. A recent example of a bottleneck study employing an intensive approach is Rudjanakanoknad (2005). The other approach might be termed the *extensive* approach, in which statistical techniques are used to try to discover relationships between the capacities and other observable characteristics of a sample of bottlenecks. In such cases, the research may be said to be extensive with respect to at least two dimensions: (*a*) the number of sites considered and (*b*) the number of daily data sets analyzed for each site. Most past research related to freeway capacity (e. g. Schoen 1995) has been basically extensive in orientation; however, (relative to what might be appropriate, given the complexity of the problem) samples have often been rather small in terms of at least one of the dimensions of extensiveness. The research described here was intended to be extensive. The original goal was to study at least 20 bottlenecks, and to collect data for at least 50 workdays at each site. As a result of difficulties to be discussed later, however, neither of these goals was entirely met.

2.1 Study Sites

As initially conceived, the study was to have involved sites in San Diego and other metropolitan areas. The use of non-local sites was intended to provide a larger sample and to avoid problems resulting from the typical location of detectors in San Diego. In the San Diego area, most loop detectors were originally installed as a part of the ramp metering system and were located immediately upstream from on-ramps. Such detectors are not actually in the suspected bottleneck sections where these are immediately downstream from on-ramps, as is often the case. It was believed initially that such sites could still be used if loop detector data were supplemented by traffic counts from videotapes.

It was assumed that the critical gaps would occur in the queue immediately upstream of the bottleneck and thus could be estimated from loop detector data, but CLFR would need to be established for the bottleneck itself. Hand counts from the videotapes could be used to determine flow ratios for a relatively small sample of time periods. These would be related to the flow ratios at the detectors upstream of the bottleneck and the relationships would then be used to estimate bottleneck flow ratios for other times.

In the case of non-San Diego sites, one selection criterion was that detectors be available in the bottleneck section. Other site-selection criteria were (*a*) evidence from speed data or other sources that an active bottleneck was present on a regular basis (that is, there was a queue upstream and no queue spillback from downstream) and (*b*) availability of loop detector data (including volumes and occupancies) on a lane-by-lane basis at a time base of one minute or less.

The initial goal was to identify at least twenty bottleneck study sites. In all cases, the "bottleneck site" should be understood to consist of the critical roadway section; given the nature of the data, it was not possible to narrow down the identification of the bottlenecks to specific locations within the sections. Twenty-five potential study sites were identified in the San Diego, Seattle, and Minneapolis-St. Paul areas. Bottlenecks in the San Diego area were identified through the study team's past experience, a list supplied by Caltrans District 11, a list developed by Chen (2004), and an analysis of lane configurations and speed data at suspected bottleneck locations. Bottlenecks in the Seattle area were identified by analysis of lane configurations and speed data and confirmed by discussions with Washington State Department of Transportation (WSDOT) personnel, and those in Minneapolis-St. Paul were selected from a list or bottlenecks previously identified by Zhang (2004a, 2004b) and verified by analysis of lane configurations and speed data.

In analyzing speed data, the pattern sought was one in which speed increased in the downstream direction, with speed at the downstream detector at or near free-flow speed, that at the bottleneck detector (if present) possibly somewhat less, and that at the upstream detector significantly less than free-flow speed (indicating the presence of a queue). At some sites, low speeds were observed at the downstream detector some time after initial flow breakdown (indicated by a speed drop at the upstream detector); these speed drops indicated that queues from downstream were approaching the bottleneck section. Such sites were retained if there appeared to be a significant period during which the local bottleneck was active before the queue spillback deactivated it.

Subsequent data analysis showed that gaps in the queue upstream of the bottleneck did not correlate well with those in the bottleneck. As a result, all but three of the San Diego study sites had to be excluded from the portion of the study that developed the capacity models. These sites were used, however, for portions of the study that considered the bottleneck capacities themselves and their variability, and were used to verify the predictive relationships developed using the other sites. The result was that of the 25 sites originally identified, 15 were available for the initial development of predictive relationships; however, one of these was subsequently excluded because the data appeared to be anomalous. This left 14 sites to be used in calibrating the final versions of the models plus the 6 additional sites used for model verification. The remaining four sites could not be used at all either because of chronic problems with data quality or data availability or because subsequent evaluation indicated that they were not independent, active bottlenecks.

Table 1 lists the study sites, describes them in terms of the peak period involved, the number of lanes and the bottleneck type, and notes the how each site was used in the analysis. Site designations consist of the prefix MN, SD, or WA (for Minneapolis-St. Paul, San Diego, and Seattle respectively) and a number; in the case of Minneapolis-St. Paul, the sites are identical with some of those used by Zhang (2004a, 2004b), and the numbers are the same as those used in these papers. Figures 1 and 2 show schematic diagrams of the sites. These diagrams identify the freeway, direction, lane configuration, and upstream and downstream interchanges bounding the site. The heavy vertical lines mark the approximate location of the bottleneck.

Bottleneck type classifications for Minneapolis-St. Paul were derived from Zhang (2004a). Those for San Diego were based on direct observation and analysis of lane configurations and those for Seattle on discussions with Washington State Department of Transportation personnel and analysis of speed data and lane configurations. Given the geographical scope of the project, it was not possible to determine the bottleneck locations and causes in great detail; consequently, the possibility exists that some bottlenecks were misclassified. Site WA-4 is of particular concern. In this case, the queue appears to form in the section just upstream of the weaving section, and this is shown as the bottleneck in Figure 1. The only logical cause for a bottleneck at this location is

Table 1 Study Site Characteristics

Site	Peak	Lanes	Type	Status
MN-02	PM	2	merge	used to develop relationships
MN-08	PM	3	merge	used to develop relationships
MN-14	PM	3	merge	used to develop initial relationships
MN-18	PM	2	merge	used to develop relationships
MN-21	PM	2	merge/horizontal curve	used to develop relationships
MN-22	PM	2	merge	used to develop relationships
MN-23	PM	3	merge/3-d curve	used to develop relationships
MN-25	PM	2	lane drop	used to develop relationships
MN-26	PM	4	merge/3-d curve	not used – not active bottleneck
SD-01	AM	4	merge/grade	used for verification only
SD-02	AM	4	merge	used for verification only
SD-03	AM	4	merge/grade	used for verification only
SD-04	AM	4	merge	not used – not independent of site 3
SD-05	AM	4	weave exit leg, grade	used to develop relationships
SD-06	PM	4	merge/grade	used for verification only
SD-07	PM	4	weave exit leg	used to develop relationships
SD-08	PM	4	weave exit leg, grade	used to develop relationships
SD-09	AM	4	merge	used for verification only
SD-10	PM	4	merge/weave	not used – under construction
SD-11	PM	4	merge	not used – bad data
SD-12	PM	5	merge or grade	used for verification only
WA-01	PM	3	merge	used to develop relationships
WA-02	PM	2	diverge	used to develop relationships
WA-03	PM	3	merge	used to develop relationships
WA-04	AM	2	weave	used to develop relationships

weaving, however, and the most likely location for the critical point (based on the lane configuration) is the upstream end of the weaving section. Still images of traffic at this site are available on the internet (WSDOT 2005); however, review of these did not resolve the question of exactly where flow was breaking down.

2.2 Data and Data Sources

Data collected included the following:

- Loop detector data, including volume and occupancy
- Vehicle classification data
- Census data

Figure 1 Schematic Diagrams of Sites Used for Development of Relationships

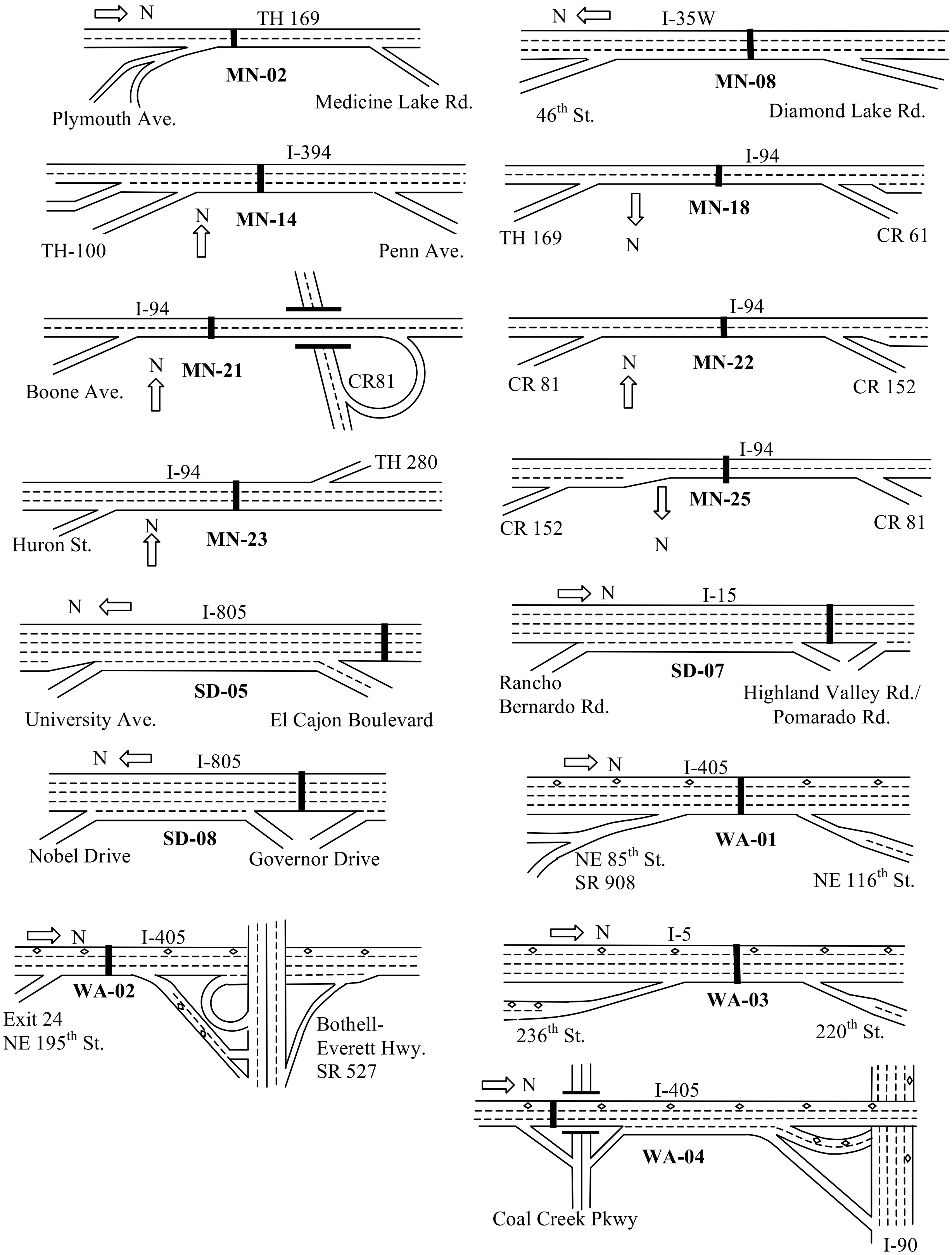
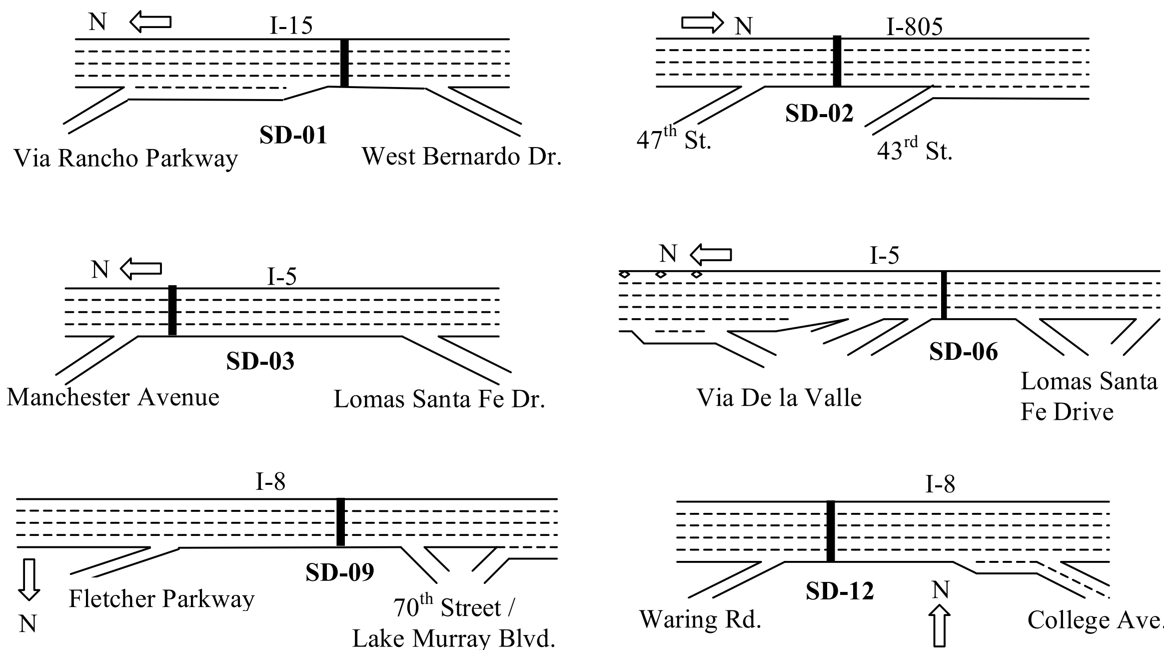


Figure 2 Schematic Diagrams of Sites Used for Verification of Relationships Only



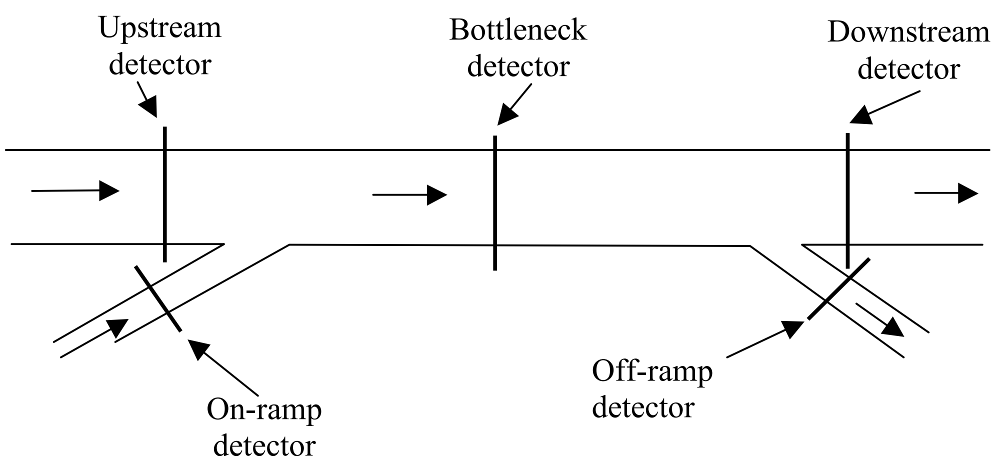
- Geometric data, including lane configurations and grades
- Rainfall data
- Incident log data

2.2.1 Loop Detector Data

Loop-detector data were collected for each site. In the case of Minneapolis-St. Paul, data were available for two different periods, October 16 – December 1, 2000 and June 1 – August 27, 2004; data from the fall of 2000 were collected during an experiment in which ramp meters were turned off, and those collected during the summer of 2004 represent a period during which the meters were in operation. Data for San Diego and Seattle sites were collected for 60 or more weekdays during the summer of 2004. Because of the difference in metering status, the 2000 and 2004 data from Minneapolis-St. Paul were treated separately in the analysis; as a result of data quality problems, however, both periods could be analyzed for only three of the sites (MN-2, MN-14, and MN-23). This resulted in a total of 18 combinations of site and data collection period available for development of predictive relationships plus 6 more that could be used for verification.

Loop detector data were sought for three locations at each site: the bottleneck section itself and the detector stations immediately upstream and downstream. Data from the upstream station were used to verify existence of a queue, and data from the downstream station were used to screen for bottleneck deactivation by growth of queues from downstream. Where there were no detectors in the bottleneck section itself, data were collected from the detector stations immediately upstream and downstream, and the bottleneck flow was calculated by summing the mainline flow at the upstream station and the on-ramp flow. Figure 3 is a schematic diagram showing the typical ramp and detector layout.

Figure 3 Typical Ramp and Detector Locations



Loop detector data for the San Diego sites were obtained directly from Caltrans District 11. Initially, data for the Minneapolis-St. Paul sites were obtained directly from Lei Zhang and David Levinson of the University of Minnesota; subsequently, these data became available through internet sites maintained by the University of Minnesota at Duluth (TDRL 2005a, 2005b). Data for the Seattle sites were provided by a web site maintained by the University of Washington (2005). In all cases, data included volumes and occupancies for individual lanes. The time base for these counts was 30 s for San Diego and Minneapolis-St. Paul and 20 s for Seattle.

Gaps, lane flow ratios, and estimated speeds were derived from the volumes and occupancies. Gaps were calculated by

$$\bar{g}_i = \frac{1-\Omega_i}{q_i} \tag{13}$$

where $\bar{g}_i$ = average time gap, lane i
Ω_i = occupancy, lane i, dimensionless ratio
q_i = flow rate, lane i

Lane flow ratios were calculated by

$$r_i = \frac{q_i}{\bar{q}} \tag{14}$$

where r_i = flow ratio, lane i
q_i = flow rate, lane i
$\bar{q}$ = flow rate averaged across all lanes

Estimated speeds were calculated by

$$\hat{u} = \frac{\ell \sum_i q_i}{\sum_i \Omega_i} \tag{15}$$

where $\hat{u}$ = estimated speed
ℓ = average effective vehicle length, assumed to be 7.5 m

2.2.2 Rainfall Data

Rainfall data consisting of hourly precipitation records for Minneapolis and Seattle were used to identify periods with precipitation. These data were obtained from the National Climatic Data Center (National Oceanographic and Atmospheric Administration 2000, 2004a, 2004b). In the case of San Diego, periods with precipitation were identified by direct observation.

2.2.3 Incident Data

In the case of San Diego, incident log data were used to identify periods during which flow may have been affected by incidents. These data were generated by the California Highway Patrol Computer-Aided Dispatch System and provided by the Freeway Performance Management System (PeMS 2005). In addition, an incident detection flag is included in the Seattle data. This flag was never found to be set, however, so it does not appear that it is actually used.

2.2.4 Geometric Data

Geometric data, including lane configurations and grades, were used to classify the bottleneck sites and as potential explanatory variables. These data were obtained from the applicable state departments of transportation, except that in the case of San Diego, lane configurations were determined by direct observation.

2.2.5 Vehicle Classification Data

Vehicle classification data were obtained from the applicable state department of transportation for each metropolitan area. In the case of Seattle, data were obtained directly from WSDOT. Data for San Diego and Minneapolis-St. Paul were obtained from web sites (California Department of Transportation 2005, Minnesota Department of

Transportation 2002). Unfortunately, the exact classification schemes are different for each of the states concerned, and none is really compatible with that used by the HCM. In the case of Washington State, large vehicles are classified by length, and data are available by time of day on an hourly basis. In the case of California, vehicles are classified by the number of axles, and data are available only as annual average daily traffic volumes. In the case of Minnesota, data are available as average daily traffic volumes for all traffic versus heavy commercial vehicles, which are defined as those with six or more tires. In no case are recreational vehicles treated as a separate category. In the case of San Diego, data supplied by Caltrans were supplemented by hand counts taken from videotapes. These were taken during the applicable peak periods and classified vehicles as (*a*) passenger cars; (*b*) vans, light trucks, and sport utility vehicles; (*c*) recreational vehicles; and (*d*) trucks. All analysis was based on 24-hour counts, since this was the only type available for all sites. For each site, the vehicle classification data used were those from the nearest available count station.

2.2.6 Census Data

Census data were used to characterize driver populations. These data were downloaded from a web site maintained by the U. S. Census Bureau (2005). Socio-economic characteristics of the driver populations were estimated by defining a region consisting of several census tracts that were judged to be a plausible commuter-shed for each study site. In the case of morning peak sites, these regions are upstream from the site, and in the case of evening peak sites, they are downstream. In defining the commuter sheds, the following rules were employed: (*a*) in the absence of other constraints, zones were approximately 15 km long by 6 km wide, centered on the freeway in question; (*b*) where there were parallel freeways less than 12 km away, the zone boundary was placed approximately halfway between the two freeways; (*c*) where applicable, zones were limited by major traffic barriers and by the edge of the urbanized area; (*d*) if the upstream end of the zone, as determined by the 15 km rule, included a central business district (CBD), the zone was terminated at the CBD; and (*e*) census tracts were included if more than half of their area was within the zone boundaries as determined by rules (*a*) through (*d*). Appendix A documents the census tracts included in each bottleneck commuter shed.

For each set of census tracts, the following classification tables were downloaded: (*a*) sex by age, (*b*) sex by educational attainment for the population 25 years or older, (*c*) family type by number of workers in family, (*d*) sex by occupation for employed civilian population 16 years and older, and (*e*) household income. From these classification tables, a summary was prepared for each set of census tracts; this summary includes (*a*) percent males, (*b*) percentage distribution of age, (*c*) percentage of high school and college graduates, (*d*) percentage of households with 1, 2 and 3 or more workers, (*e*) percentage distributions of types of occupations (managerial/professional, service, office and administrative, agricultural, construction, production, and material moving), (*f*) median household income, and (*g*) median age.

Data Reduction

Reduction of traffic data included data extraction and collation, data screening, identification flow periods representing different flow conditions, and calculation of derived flow characteristics such as CLFR and gap.

As previously described, loop detector data for the project were obtained from sites in three different metropolitan areas. The structure and format of the data files as originally downloaded differed depending on the source. Consequently, the first step in the reduction of the data was to use custom data extraction and reduction software to (*a*) extract the data from larger files, (*b*) screen it, (*c*) calculate derived measures (see Section 2.2 for formulas), and (*d*) arrange the data from different sources in a common format. This software produced a single text file for each daily peak period at each study site. Spread sheets were then used for detailed analysis of the daily bottleneck data files.

2.3.1 Data Screening and Evaluation of Data Quality

Loop detector data are subject to a variety of types of errors (Chen 1987, Jacobson 1990). These include missing data, obviously corrupt data, and less-obvious count biases. As a part of the data-reduction process, data sets were screened for missing or obviously corrupt data. Screening tests were carried out for data from individual lanes and included: (*a*) missing data, (*b*) excessive volume/occupancy ratio (estimated speed greater than 150 km/h where the vehicle count was 8 or more), (*c*) estimated gap too small (estimated gap less than 0.5 s), (*d*) speed in lane inconsistent with speed averaged for all lanes, (*e*) volume and occupancy identical for two or more successive count intervals, and (*f*) in the case of San Diego, a bad-data flag set by the Caltrans district. In all cases except that of volumes and occupancies identical in successive time periods, data were eliminated and replaced by a flag if they failed the data screening test. In the case of identical data in successive time periods, the data were retained but flagged. This condition was particularly prevalent for the Seattle data, where it apparently represents either some kind of detector error that is not identified by the system's data screening algorithms or an error in polling the detector cabinets (e-mail, Joel Bradbury, TDAD, 4/12/05).

In addition to relatively obvious cases of corrupt data, there was evidence of count biases at individual detector statioins. Where possible, cumulative counts taken at successive stations were compared to determine the relative biases between them. For each pair of stations compared, data were selected for five days during which the sites were uncongested at both the beginning and end of the data collection period, and the counts for the entire data collection period were compared. Table 2 summarizes results of these comparisons. Discrepancies between counts at adjacent detector stations range from less that 0.1 percent to a little more than 6.5 percent. Where counts disagreed, it was clear that data were biased for at least one station, but not whether one or both stations were biased, which station was biased (if only one), nor what the true count should have been.

Table 2 Cumulative Flow Comparisons for Adjacent Detector Stations

	Detector station number		Percent discrepancy		
Site	Upstream	Downstream	Maximum	Minimum	Average
MN-02	769	770	0.11	0.01	0.09
MN-08	54	55	3.96	3.26	3.53
MN-14	282	284	2.55	2.16	2.29
MN-18	220	218	-0.04	-0.34	-0.26
MN-21	223	225	0.70	-0.31	0.10
MN-22	229	231	1.23	0.47	0.83
MN-23	467	775	2.67	1.29	2.17
MN-25	232	230	0.39	0.17	0.28
SD-01	149	148	0.56	-0.34	-0.02
SD-03	108	107	3.85	1.18	2.70
SD-05	68	67	0.24	-0.24	-0.02
SD-06	130	132	7.17	6.09	6.56
SD-08	300	71	-0.42	-1.50	-1.10
WA-01	720	722	3.16	2.03	2.54
WA-02	752	754	-1.00	-1.69	-1.43
WA-03	184	186	-1.67	-2.42	-1.89
WA-04	667	672	-0.89	-1.36	-1.21

2.3.2 Identification of Flow Periods

The first step in the analysis was to determine periods representing different flow conditions within each daily peak period at each bottleneck. Past research regarding bottleneck performance has established that the highest flows usually occur immediately prior to flow breakdown and past authors have proposed different definitions of capacity based on the existence of high-volume PQF and QDF periods (see Section 1.1). The approach used here was to analyze pre-queue and queue discharge periods separately. In addition, cases were observed in which high-volume uncongested flows persisted for extended periods of time without flow breakdown or in which queues dissipated and then reformed. In the latter case, it was sometimes clear that demand flow had dropped and later increased to produce a second period of PQF; in other cases the flow did not appear to increase prior to the formation of the second queue. The existence of high-volume uncongested flow periods that were not obviously PQF eventually led to a fourfold classification of high-volume flow periods:

1. *QDF* – any period during which the bottleneck was active – that is, there was evidence of a queue upstream and no evidence of interference from queue spillbacks from downstream.

2. *PQF* – any period of near-constant flow preceding local flow breakdown. Note, this definition is not the same as that of Zhang (2004a), in that it does not require the flow rate during a period of PQF to exceed the average queue discharge rate.

3. *Non-queue flow (NQF)* – any period of high-volume near-constant flow that did not result in flow breakdown.

4. *Inter-queue flow (IQF)* – Any period of high-volume flow between the dissipation of one queue and the formation of another for which there was not a distinct increase in flow prior to the formation of the second queue.

Although all four types of flow were identified and recorded, only PQF and QDF were considered in the analysis.

The beginnings and ends of periods of QDF were determined from plots of time series of estimated speeds and re-scaled cumulative speeds. Re-scaled cumulative speed was calculated as

$$S(T) = \sum_{t=1}^{t=T-1} \left[\hat{u}(t) - \rho \right] \tag{16}$$

where $S(T)$ = re-scaled cumulative speed prior to time T
$\hat{u}(t)$ = estimated speed for time interval t
ρ = a re-scale factor used to rotate the curve

The advantage of the re-scaled cumulative function is that it smoothes the data while allowing changes in average speed (indicated by changes in the slope of the plot) to be detected very precisely. The degree of rotation was chosen so as to make changes in average speed more obvious while retaining the smoothing effect (Cassidy 1995).

Estimated speeds and re-scaled cumulative speeds were plotted for locations upstream of, downstream of, and in the bottleneck sections (where data for all these locations were available). Rapid decreases in speed at the upstream station indicated the beginning of the queue and subsequent rapid increases in speed accompanied by decreases in flow (or other indications of bottleneck deactivation) indicated its end. In a few cases where upstream detectors were a considerable distance from the point of flow breakdown, minor decreases in speed at the bottleneck station were used to indicate the beginning of the queue, and minor increases in speed accompanied by decreases in flow to indicate its end. Re-scaled cumulative speed plots for downstream detector stations were used to identify cases of bottleneck deactivation by queues from downstream.

Where available, incident logs were consulted to help identify periods during which bottlenecks were deactivated or flows may have been affected by incidents; such time periods were excluded. Also, periods affected by rainfall were excluded. In the case of San Diego, periods of precipitation were identified by direct observation (there were none during summer 2004); for sites in the Minneapolis-St. Paul and Seattle areas, periods of precipitation were identified from the hourly precipitation summaries described in Section 2.2.2. Time periods were excluded if any precipitation was recorded.

In most cases, the end of the period of PQF was taken to be the beginning of the period of QDF, as indicated by the speed time series and re-scaled cumulative speed plot. The beginning of the period of PQF was determined from plots of re-scaled cumulative flows. Re-scaled cumulative flow was calculated as

$$N(T) = \sum_{t=1}^{t=T-1} \left[q(t) - \rho \right] \tag{17}$$

where $N(T)$ = re-scaled cumulative flow prior to time T
$q(t)$ = flow for time interval t
ρ = a re-scale factor used to rotate the curve

As in the case of re-scaled cumulative speed plots, changes in the slope indicate changes in the mean flow rate; the object in this case was to identify that period (if any) immediately prior to flow breakdown for which the re-scaled cumulative plot had a near-constant slope. Figure 4 shows an example of the re-scaled cumulative speed and flow plots and illustrates the identification of periods of PQF and QDF.

Note that re-scaled cumulative flow curves can also be used to identify changes in vehicular storage within sections provided all the flows into and out of the section are counted (Cassidy 1995). This procedure is an alternative to use of speed-based analysis to identify the location of bottlenecks and the time of flow breakdown. In some cases it may be more accurate, but it is subject to errors and uncertainties because free-flow travel times and bias correction factors must be estimated from the data. In addition, it is significantly more time consuming than speed-based techniques. The cumulative flow technique was not used in this study because the potential increase in accuracy did not appear to be worth the very significant increase in the effort that would have been involved.

2.3.3 Calculation of Flow Characteristics

Once periods of PQF and QDF were identified, the following were calculated for each period:

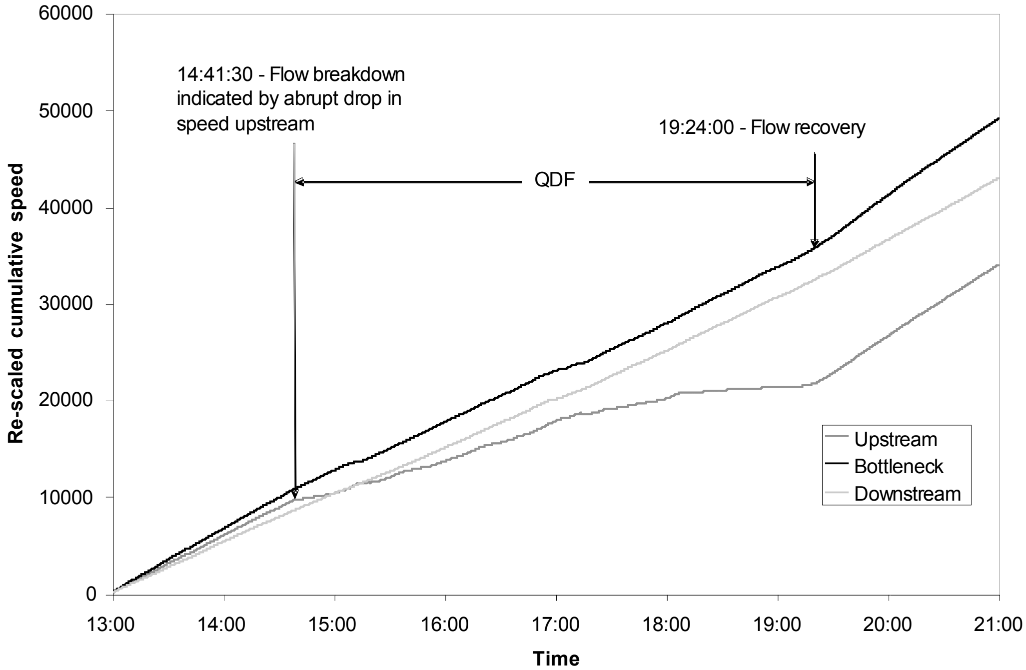
1. Mean and standard deviation of

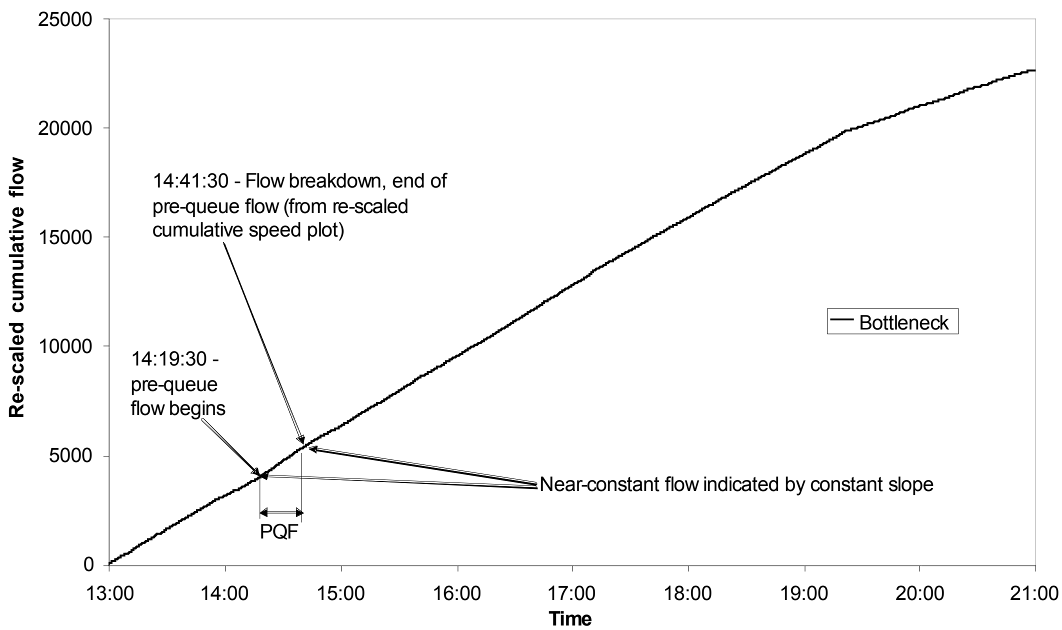
   (*a*) Flow per lane through the bottleneck

   (*b*) Flow ratios and gaps for each lane for the bottleneck station, if available

   (*c*) Gaps for each lane at the upstream detector station

Figure 4 Identification of Flow Periods





2. Mean flow for the upstream on-ramp and downstream off-ramp, if present.

The lane flow ratios were used to identify the critical lane for each time period. Once the critical lane was identified, the means and standard deviations of the CLFR and the gaps (upstream and at the bottleneck) were noted and the means of the critical lane headway and passage time were calculated. Summary files maintained for each site were then used to record:

1. Type, time limits, and duration of the flow period
2. Mean and standard deviation of bottleneck flow per lane
3. Mean and standard deviation of CLFR
4. Mean and standard deviation of gaps (upstream and bottleneck)
5. Mean critical lane headway
6. Mean critical lane passage time
7. Mean on-ramp and off-ramp flows

2.4 Statistical Analysis

2.4.1 Underlying Statistical Models

The statistical models underlying data analysis are summarized below. Key assumptions include:

1. PQF and QDF are assumed to be distinct flow conditions, for which typical flow rates vary among bottlenecks. Typical values of CLFRs, gaps, critical lane passage times, and the ratios of arithmetic mean flow to harmonic mean flow are also assumed to vary among bottlenecks.

2. Raw 20 s or 30 s traffic counts may be grouped into periods corresponding to individual episodes of PQF and QDF. It is assumed that data collected during these episodes represent samples from populations of flow characteristics that are peculiar to the site and that these individual samples can be merged to estimate the overall distributions of the flow characteristics. The mean values of these merged samples represent the site's flow characteristics.

3. Non-site-specific relationships between mean PQF and mean QDF respectively and the site-mean flow characteristics are assumed to exist. Equation 11 gives an a priori relationship that applies to any site if r_c, $\overline{p}_c$, $\overline{g}_c$, and α are known, but because r_c, $\overline{p}_c$, and $\overline{g}_c$ may be interrelated, it may be possible to simplify the relationship. If simpler relationships do exist, they may apply either to all bottlenecks or to subsets of bottlenecks – for instance, all merge bottlenecks.

4. Non-site specific relationships also exist between the site-mean flow characteristics and other characteristics of the sites such as driver population characteristics, vehicle population characteristics, lane configurations, and

geometric design features (for instance, vertical alignment). These relationships can form the basis for predictive models that will explain a significant amount of the variation in PQF and QDF among different bottlenecks.

5. Driver population characteristics can be inferred from available data, such as census data for areas that constitute logical commuter sheds for individual bottlenecks.

Several of these underlying assumptions are subject to verification. For instance, it is possible to verify the statistical significance of differences in site-mean PQF and QDF rates at individual sites, differences among sites in site-mean flow characteristics, and correlations among flow characteristics and between specific flow characteristics and other site characteristics. By comparing models that incorporate intervening variables with ones that do not, it is also possible to determine whether use of two-stage models can improve predictive models of bottleneck capacity.

2.4.2 Calculation and Analysis of Site-Mean Flow Characteristics

Once the data collection and reduction described above were complete, data for individual sites were reduced to site-level means and (for some data types) standard deviations. Since the underlying model was that the data representing individual flow periods were samples from populations of PQF and QDF characteristics, the means and standard deviations for the individual flow periods were combined as follows to produce means and standard deviations for the sites:

$$\bar{x} = \frac{\sum_i n_i \bar{x}_i}{\sum_i n_i} \tag{18}$$

and

$$s_x = \sqrt{\frac{\sum_i (n_i - 1) s_{xi}^2}{\sum_i n_i - 1}} \tag{19}$$

where $\bar{x}$ = site-level mean of x
$\bar{x}_i$ = mean of x for flow period i
s_x = site-level estimate of the standard deviation of x
s_{xi} = estimated standard deviation of x for time period i
n_i = number of count intervals in flow period i

Once site-mean values of the flow characteristics had been determined, average PQF and QDF for each site were compared with one another to verify that they were distinct flow conditions. This involved (*a*) calculation of the difference between PQF and QDF as a percentage of average PQF and (b) use of *t*-tests to determine whether differences in site-mean PQF and QDF were statistically significant. Also, the homogeneity of PQF and QDF as flow conditions was evaluated by using analysis of variance to determine the statistical significance of differences in mean PQF and QDF for different flow periods at the same site. Other data analyses focusing on individual sites included analysis of the relationship between gaps at detector stations in and upstream from the bottleneck (see Section 2.1), analysis of possible variations in QDF by time of day at sites where queuing lasted for several hours, and analysis of the relationship between the pre-queue flow rate and the duration of PQF (VidhyaShankar 2005, Ramakrishnan 2006).

2.4.3 Relationships among Flow Characteristics at Different Sites

Site-mean flow characteristics were analyzed to identify relationships among them. These analyses compared the characteristics of PQF with those of QDF, and, for PQF and QDF considered separately, the relationships between individual flow characteristics. As a first step, analysis of variance was used to verify that their differences from site to site were statistically significant. Following this, scatter plots were prepared and correlation coefficients were calculated to identify significant relationships. Where appropriate, least-squares regression analysis was used to quantify relationships. Univariate relationships between PQF and QDF flow were investigated for the following pairs of characteristics:

- Flow per lane
- Average critical lane flow
- Gap
- Average CLFR

Relationships between the following pairs of characteristics were analyzed separately for PQF and QDF:

- CLFR and flow per lane
- Gap and flow per lane
- Passage time and flow per lane
- Gap and CLFR
- Gap and passage time
- Gap and critical lane average flow
- Passage time and critical lane average flow
- Gap and critical lane average headway
- Passage time and critical lane average headway
- CLFR and upstream on-ramp flow as a fraction of total flow in the bottleneck section
- CLFR and downstream off-ramp flow as a fraction of total flow in the bottleneck section

2.4.4 Relationships between Flow Characteristics and Other Site Characteristics

Section 1.3 concluded with a number of hypotheses that outlined expected relationships between the various flow characteristics and the geometric, vehicle population, and driver population characteristics of the sites. The hypotheses provided the starting point for the analysis of these relationships, guiding the choice of data to be collected and the initial formulation of explanatory models.

Section 2.2 describes the various types of data collected. Data related to site characteristics included lane configurations and geometric characteristics (length and steepness of grades in and just upstream of the bottlenecks sections), vehicle classification data (percentage of large vehicles), and various items of census data possibly indicative of driver population characteristics. The proportion of heavy vehicles in the traffic stream and the length and steepness of grades were used to calculate heavy vehicle factors as defined in the HCM, using Eq. 4 with $P_R = 0$ and P_T equal to the proportion of heavy vehicles given by the 24-hour classification counts. Specific census data items used in the analysis included median age, median income, the percentage of college graduates in the commuter-shed zone, population density, and the percentage of males aged 18 to 24 years. This last item was selected (somewhat arbitrarily) to represent aggressive drivers, since insurance companies tend to associate this group with a high risk of accidents.

As a first step in the analysis of the site data, correlation coefficients were calculated for various pairs of potential explanatory variables to get some idea of the degree to with they were interrelated. Following this, univariate relationships between flow characteristics and the potential explanatory variables were investigated by calculating correlation coefficients and preparing scatter plots.

On the basis of this analysis, nine of the most promising explanatory variables were selected and evaluated by means of stepwise regression. This process resulted in selection of the one or two most significant explanatory variables in each case. Multivariate regression was then carried out to quantify the relationships between these explanatory variables and the flow characteristics. These relationships were then tested for their sensitivity to data suspected of being anomalous by omitting such data and repeating the stepwise regression and multivariate regression analyses.

Finally, the most promising relationships were used to calculate estimated PQF and QDF for the sites used in developing the analysis and the six additional "verification sites" in San Diego. These estimated flows were compared with the measured flows to determine how well the models performed. In addition, the capacities of the bottlenecks were estimated using the existing HCM methods, and these estimated capacities were compared with both the measured flows and those estimated with the models.

3. RESULTS

3.1 Flow Characteristics

Important characteristics of the individual study sites include the site-level means and standard deviations of flows, and the means of gaps, critical lane average passage times, and CLFRs. Statistics for these characteristics were calculated separately for PQF and QDF. For merge bottlenecks, on-ramp and off-ramp flows as a percentage of the total bottleneck flow were also calculated. Detailed tables summarizing these characteristics may be found in Appendix B, Tables B1 – B5.

Sample sizes are listed in the tables in Appendix B. These are given as the total number of periods of PQF or QDF that were recorded for each site and vary depending on the site and data collection period. For all three metropolitan areas, data were collected at each site for more than 60 days during the summer of 2004; however, the number of days with useful data was somewhat less because of missing data, detector malfunctions, and days excluded because of weather. Data from the fall 2000 for the Minneapolis-St. Paul sites were limited to a maximum of 28 days because of the limited duration of the experiment in which the ramp meters were turned off; as in the case of the summer of 2004, some sites recorded considerably less data because of problems with the data collection system. The actual number of periods of PQF and QDF differs from the number of usable daily data sets because periods of PQF and/or QDF were not observed on some days and multiple periods were observed on others.

Mean PQF ranged from 1,686 veh/h/lane at site MN-14 during the summer of 2004 to 2,419 veh/h/lane at site SD-01. Note, however, that the lowest average flow was based on only six observations and hence is not well established; the second lowest PQF was 1,824 at the same location during fall 2000. Coefficients of variation for PQF ranged from 0.10 to 0.22. Mean QDF ranged from 1,647 veh/h/lane at site MN-14 during the summer of 2004 to 2,184 veh/h/lane at site SD-02. Coefficients of variation for QDF ranged from 0.07 to 0.18, which indicates that the variation in QDF is slightly less than that in PQF.

One of the underlying statistical assumptions of the study was that PQF and QDF represent distinct flow conditions and that flow characteristics for individual periods of PQF or QDF represent samples from overall populations of flow characteristics.

To test the hypothesis that PQF and QDF represent distinct flow conditions, site-mean PQF was compared with site-mean QDF. As was expected from the results of past research, PQF exceeded QDF for all combinations of site and data collection period. The mean flow decreases experienced in the transition from PQF to QDF ranged from 1.8 percent at site MN-23 during summer 2004 to 15.4 percent at site WA-04. The significance of the difference in mean PQF and mean QDF at each site was investigated by means of *t*-tests. In all cases but one (MN-14 for the summer of 2004) the differences were significant at the 0.01 level. From this result, it may be concluded that PQF and QDF are indeed distinct flow conditions.

Analysis of variance was used to investigate whether there were statistically significant differences in mean flow for different episodes of PQF and QDF at the same site. For each site, differences in mean flow during individual episodes of QDF were highly significant. In most cases, this was also true of PQF. Exceptions include sites MN-14 and MN-23 in 2004 and site SD-09. From this result, it may be concluded that although distinct, PQF and QDF are not necessarily homogeneous flow conditions. Details of the comparisons of site-mean PQF with the corresponding QDF and the analysis of variance for individual flow periods are given in Appendix B, Tables B6 – B8.

In the case of three of the sites in Minneapolis-St. Paul, data were available for both the fall of 2000, when the ramp meters were turned off on an experimental basis, and the summer of 2004. Zhang (2004b) has previously reported that flows at these bottlenecks (both PQF and QDF) were greater before the ramp meters were turned off than during the experiment, thus supporting the idea that ramp metering was somehow increasing the capacities of the bottlenecks. Tables B1 and B2, on the other hand, show that at all three sites, both PQF and QDF were lower in summer 2004 (with the meters on) than in fall 2000. The statistical significance of these decreases in flow was investigated by means of *t*-tests. Results are summarized in Appendix B, Table B9; these results demonstrate that the decreases were highly significant in all cases.

The standard deviations of PQF and QDF in Tables B1 and B2 are for samples of all the individual 20-s or 30-s counts for each site. The level of variation in the mean flow for different periods of PQF and QDF each site may also be of interest. Means, standard deviations, and coefficients variation of the mean flow during individual periods of PQF and QDF at the various sites are summarized in Appendix B, Table B10. Coefficients of variation for mean flows during individual flow periods range from 0.02 to 0.08 in PQF and from 0.02 to 0.06 in QDF. These coefficients of variation give a sense of the level of the day-to-day variation in mean flow rates at individual sites.

3.2 Variations in Queue Discharge by Time of Day

Inspection of re-scaled cumulative flow plots suggested that there might be fairly consistent time-of-day variations in QDF at several of the sites. This was particularly the case at morning peak sites where congestion extended well beyond the normal commute trip peak. To explore the possibility that there were significant variations in QDF by time of day, five sites with especially long congested periods were selected, and QDF from different days was averaged by time of day, using 30-minute averaging intervals. Analysis of variance indicated that there were, indeed, significant time of day variations in QDF at these sites, with the maximum flow rate occurring early in the peak at morning peak sites and late in the peak at evening peak sites. It is plausible that these variations in QDF are related to the presence of commuter traffic; however, the interrelationships among time-of-day variations in flow, CLFR, and gap varied among the sites, suggesting that the behavioral basis of any correlation between commuter traffic and high QDF is not simple. Hence the hypothesis that gaps will be smaller during work trip peaks than at other times is not altogether supported by the data. Appendix C gives details of this analysis and its results.

3.3 Relationships among Flow Characteristics

As a first step in the analysis of relationships among site-mean flow characteristics at different sites, analysis of variance was used to verify that their differences from site to site were statistically significant. Table 3 summarizes the results and shows that for both pre-queue and queue discharge conditions, differences among the sites in flows, gaps, and CLFRs were all highly significant.

Table 3 Results of Analysis of Variance of Site-Mean Flow Characteristics

		Degrees of freedom		
Measure	F	p – 1	N – p	Level of significance
Pre-queue				
Flow	55.73	17	21,251	3.8×10^{-186}
Flow ratio	188.00	17	21,266	0
Gap	104.36	17	21,266	0
Queue discharge				
Flow	3,856.22	17	251,801	0
Flow ratio	1,488.77	17	250,235	0
Gap	1,753. 24	17	250,235	0

Site-mean flow characteristics were then analyzed to identify relationships among them. This involved calculation of correlation coefficients to determine (*a*) whether the intervening variables are interrelated and (*b*) which intervening variables are most strongly associated with average PQF and QDF. First, the correlation for PQF and QDF was calculated and found to be significant at the 0.01 level. This indicates that sites that have high values of PQF also have high values of QDF, so that similar site features presumably affect both. Correlation coefficients were also calculated to compare other PQF characteristics (critical lane flow, gap, passage time, and CLFR) with similar characteristics in QDF. In all cases, the PQF characteristics were highly correlated with the corresponding QDF characteristics, once again implying that similar site conditions affect both PQF and QDF characteristics.

Next, the relationships between the site-arithmetic-mean flow per lane and the different intervening variables were investigated. As shown in Table 4, there is

- A negative correlation between flow per lane and gap that is significant at the 0.01 level for both PQF and QDF
- A negative correlation between flow per lane and CLFR that is significant at the 0.05 level for QDF but not for PQF

- No significant correlation between critical lane passage times and flow per lane in either case.

These results imply that (*a*) factors that explain variations in gaps explain much, but not all, of the variation in "capacity" flows and (*b*) variations in critical lane passage times have little impact. Table 4 also shows that there are significant negative correlations between passage times and gaps at the 0.05 level for both PQF and QDF, indicating that sites with large passage times tend to have small time gaps and vice versa; however, there is no significant correlation between gaps and CLFR.

The lack of correlation between gaps and CLFR suggests that they depend on different site characteristics and can be investigated separately. If critical lanes only are considered, and passage times are relatively small compared with gaps, Equations 7 and 8 suggest that there should be a positive, linear relationship between gaps and headways and a corresponding negative, non-linear relationship between gaps and average critical lane flows – although some departure from the theoretical relationship is to be expected since Equation 7 refers to harmonic mean flow rather than arithmetic mean flow. Table 4 shows correlation coefficients for site-mean gap versus site-mean critical lane flow (arithmetic mean) and site-mean gap versus site-mean headway. For both PQF and QDF, the strongest relationship is the negative one between gaps and average critical lane flow; the correlation coefficients for the positive relationship between gaps and average critical lane headways are slightly smaller in both cases, although all four correlations are significant at the 0.01 level.

Figure 10 compares scatter plots of gap versus headway with plots of gap versus critical lane flow. Inspection of these plots does not lead to any definite conclusions as to the linearity or non-linearity of either relationship – in both cases, the scatter obscures the shape of the relationship, so that (contrary to expectation) the gap-capacity flow relationship may very well be linear. When compared, the R^2-statistics for polynomial regressions are slightly higher than those for linear regressions for all cases, but the differences do not seem to be significant. The linear regression equations are

$$q_{P,c} = 3{,}731 - 1{,}071.2g_c \tag{20}$$

where $q_{P,c}$ = critical lane PQF in veh/h
g_c = critical lane average time gap, s

and

$$q_{D,c} = 3{,}249 - 831.1g_c \tag{21}$$

where $q_{D,c}$ = critical lane QDF in veh/h

TABLE 4 Correlation Analysis Summary for Site-Mean Flow Characteristics

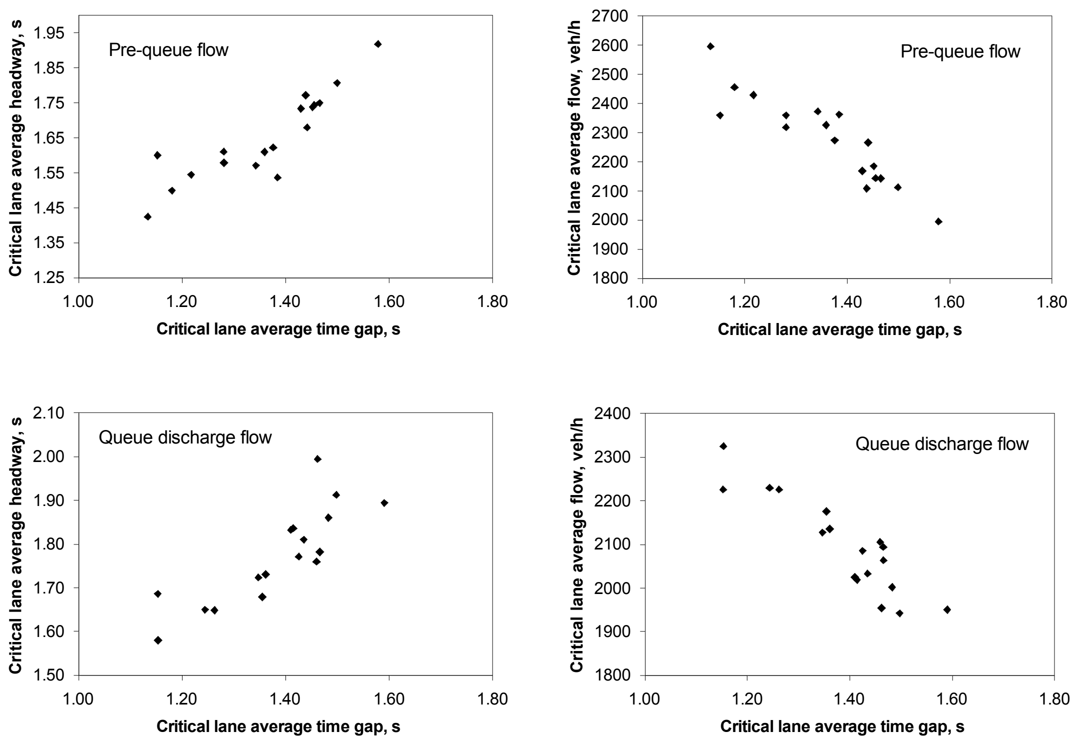
			Correlation significant?	
Relationship	Correlation coef.	Deg. of freedom	0.01 level	0.05 level
<u>Pre-queue flow</u>				
$\overline{g}_c$ vs. $\overline{q}$	-0.596	16	yes	yes
r_c vs. $\overline{q}$	-0.336	16	no	no
$\overline{p}_c$ vs. $\overline{q}$	0.009	16	no	no
$\overline{g}_c$ vs. r_c	-0.444	16	no	no
$\overline{g}_c$ vs. $\overline{p}_c$	-0.472	16	no	yes
$\overline{g}_c$ vs. $\overline{q}_c$	-0.909	16	yes	yes
$\overline{h}_c$ vs. $\overline{q}_c$	0.884	16	yes	yes
<u>Queue discharge flow</u>				
$\overline{g}_c$ vs. $\overline{q}$	-0.695	16	yes	yes
r_c vs. $\overline{q}$	-0.585	16	no	yes
$\overline{p}_c$ vs. $\overline{q}$	0.167	16	no	no
$\overline{g}_c$ vs. r_c	-0.055	16	no	no
$\overline{g}_c$ vs. $\overline{p}_c$	-0.564	16	no	yes
$\overline{g}_c$ vs. $\overline{q}_c$	-0.904	16	yes	yes
$\overline{h}_c$ vs. $\overline{q}_c$	0.823	16	yes	yes

3.4 Site Characteristics

Site characteristics include geometric characteristics, vehicle population characteristics, and driver population characteristics. Geometric characteristics include lane configurations and vertical alignment. Appendix D, Table D1 gives the numbers of lanes and the steepness and lengths of grades approaching the bottleneck section at each site. As in the case of all tables in Appendix D, the table includes both sites used in the development of the predictive models of capacity ("analysis sites") and the San Diego sites used for verification of the models ("verification sites"). In a few cases, documentation provided by the applicable state department of transportation was insufficient to determine the length of the grade. These cases are indicated in the table by question marks. In all cases they involve either downgrades or positive grades of less than 0.5 percent.

Vehicle classification data are documented in Appendix D, Table D2. Data available for all sites included the percent of heavy vehicles over a 24-hour period as determined by the applicable state department of transportation. In addition, estimates of the percentage

FIGURE 5 Scatter Plots, Critical Lane Flow vs. Gap



of heavy vehicles in the traffic stream during the applicable peak period are provided for sites in Seattle and for the analysis sites in San Diego. The table also includes an estimate of the HCM heavy vehicle factors for each site. Note that in all cases except site WA-04, the peak period heavy vehicle percentages were significantly less than the 24-hour percentages; however, the relationship between peak period heavy vehicle percentage and 24 hour heavy vehicle percentage varies among the sites. As a consequence, the heavy vehicle factors at most sites are overstated for peak period conditions.

Driver population characteristics were estimated from census data. Selected population characteristics for each site, including median income, median age, percentage of males aged 18 and 24 years, and percent college graduates, are summarized in Appendix D, Table D3.

3.5 Relationships between Site Characteristics and Flow Characteristics

Explanatory variables considered in the development of predictive models included roadway grade (GRD), percent heavy vehicles in the traffic stream (PHV), HCM heavy vehicle factor f_{HV} (FHV), median age (AGE), median income (INC), percent of males aged 18 to 24 (YML), percentage of college graduates (PCG), and population density (PDN). As a first step in determining relationships between these variables and the flow characteristics, univariate correlation coefficients were calculated for each pair of site characteristics. Table 5 summarizes this correlation analysis; as may be seen, there are a number of correlations among these variables that are significant at the 0.05 level. In particular, the HCM heavy vehicle factor has a near perfect correlation with the percentage of heavy vehicles. This resulted from the fact that the sites were relatively flat, which meant that the heavy vehicle factors were almost entirely dependent on the proportion of heavy vehicles in the traffic stream. It should also be noted that median age and median income are strongly correlated with one another, and that both have strong negative correlations with population density; there is also a weaker correlation between the population density and the number of lanes (positive). Taken together, these correlations suggest a distinction between outlying suburban sites, which have fewer lanes and serve an older and more affluent population, and higher density central city sites with the opposite characteristics.

Table 5 Univariate Correlations among Site Characteristics

Variable	GRD	FHV	PHV	AGE	INC	YML	PCG	PDN
LNS	+0.236	+0.110	-0.112	-0.467	-0.591*	+0.361	-0.417	+0.517*
GRD		-0.298	+0.296	-0.235	-0.115	+0.056	-0.231	+0.234
FHV			-1.000*	-0.184	-0.366	+0.475*	+0.408	+0.435
PHV				+0.185	+0.369	-0.474*	-0.403	-0.438
AGE					+0.798*	-0.786*	0.052	-0.715*
INC						-0.873*	-0.207	-0.878*
YML							+0.158	+0.739*
PCG								+0.019

*Indicates that correlation coefficient is significant for $\alpha = 0.05$

Tables 6 and 7 summarize univariate correlations between site characteristics and flow characteristics for PQF and QDF respectively. In the case of PQF, there are significant correlations between flow per lane and the percentage of males aged 18 to 24 (negative); critical lane flow and the percentage of college graduates (negative); gap and percentage of college graduates (positive); and between CLFR and median age (negative), median income (negative), and percentage of males aged 18 to 24 (positive). In the case of QDF, there are significant correlations between flow per lane and the percentage of males aged 18 to 24 (positive); critical lane flow and the number of lanes (positive); gap and the number of lanes (negative); and CLFR and median age (negative), median income (negative), males aged 18 to 24 (positive), and population density (positive).

Because the explanatory variables are interrelated, univariate correlations are not necessarily good indicators of their relative explanatory value. Copnsequently, stepwise regressions were used to better isolate the variables with the most influence on the flow characteristics. Separate analyses were performed for pre-queue and queue discharge conditions, and in each case relationships between the explanatory variables and flow per lane, gap, and CLFR were considered. In all cases, the level of significance for entering or removing a variable (based on its F-value) was 0.15. That is, the explanatory variable was entered or retained if the probability that it was not significant was no greater than 0.15.

Table 6 Univariate Correlations between Site Characteristics and Pre-queue Flow Characteristics

	Flow characteristic				
Site Characteristic	$\overline{q}$	q_c	g_c	p_c	r_c
LNS	+0.068	+0.391	-0.344	+0.063	+0.422
GRD	+0.327	+0.354	-0.410	+0.323	+0.061
FHV	-0.370	-0.383	+0.307	+0.017	-0.040
PHV	+0.367	+0.378	-0.303	-0.018	+0.038
AGE	+0.366	-0.023	+0.030	-0.114	-0.470*
INC	+0.417	-0.089	+0.166	-0.223	-0.614*
YML	-0.717*	-0.305	+0.214	+0.125	+0.474*
PCG	-0.334	-0.674*	+0.493*	+0.131	-0.455
PDN	-0.260	+0.064	-0.201	+0.298	+0.391

*Indicates that correlation coefficient is significant for $\alpha = 0.05$

Table 7 Univariate Correlations between Site Characteristics and Queue Discharge Flow Characteristics

	Flow characteristic				
Site Characteristic	$\overline{q}$	q_c	g_c	p_c	r_c
LNS	+0.329	+0.721*	-0.530*	-0.171	+0.386
GRD	+0.263	+0.365	-0.386	+0.297	+0.033
FHV	-0.255	-0.026	+0.032	-0.049	+0.362
PHV	+0.251	+0.022	-0.028	+0.048	-0.361
AGE	+0.141	-0.249	+0.136	-0.117	-0.513*
INC	+0.192	-0.349	+0.273	+0.031	-0.704*
YML	-0.482*	+0.021	+0.089	-0.234	+0.748*
PCG	-0.314	-0.399	+0.360	-0.054	-0.005
PDN	-0.075	+0.360	-0.303	+0.024	+0.539*

*Indicates that correlation coefficient is significant for $\alpha = 0.05$

Stepwise regression results are summarized in Table 8. The variables retained for the different cases included the number of lanes, the median income, the percentage of college graduates, and the percentage of males aged 18 to 24. On the basis of these results, median income and percentage of males aged 18 to 24 were selected to be used in multivariate regression models of flow per lane and gaps, and males aged 18 to 24 and percentage of college graduates were selected for use in similar models of the CLFR.

Table 8 Results of Stepwise Regression Analysis

Response variable	Significant explanatory variables
<u>Pre-queue flow</u>	
$\overline{q}$	YML, INC
$\overline{g}_c$	PCG
r_c	INC, PCG
<u>Queue discharge flow</u>	
$\overline{q}$	LNS, YML
$\overline{g}_c$	LNS
r_c	YML

The resulting regression equations are as follows:

$$\overline{q}_P = 2959 - 10.20\mathrm{INC} - 88.96\mathrm{YML} \tag{22}$$

$$\overline{q}_D = 2806 - 10.93\mathrm{INC} - 77.80\mathrm{YML} \tag{23}$$

$$\overline{g}_{P,c} = 0.0912 + 0.0182\mathrm{INC} + 0.0954\mathrm{YML} \tag{24}$$

$$\overline{g}_{D,c} = 0.2486 + 0.0169\mathrm{INC} + 0.0816\mathrm{YML} \tag{25}$$

$$r_{P,c} = 1.165 + 0.0161\mathrm{YML} - 0.00457\mathrm{PCG} \tag{26}$$

$$r_{D,c} = 1.013 + 0.0186\mathrm{YML} - 0.00093\mathrm{PCG} \tag{27}$$

There is reason to suspect that CLFR is related to traffic flow patterns as well as other site characteristics. Specifically, CLFR may be influenced by on-ramp and off-ramp flows. Relationships between CLFR and the ratios of on-ramp and off-ramp flow to total flow (r_{on} and r_{off} respectively) were analyzed for merge and diverge bottleneck sites. Other types of bottlenecks were not included in this analysis because the ramp configurations do not involve an on-ramp immediately upstream of the bottleneck section and an off-ramp immediately downstream from it, as is the case with most of the merge and diverge bottlenecks. Table 9 summarizes univariate correlation coefficients for CLFR versus the ratios of on- and off-ramp flow to total flow.

Multiple regression equations for CLFR as a function of on- and off-ramp flow ratios are

$$r_{P,c} = 1.099 + 0.345 r_{P,\mathrm{on}} - 0.302 r_{P,off} \tag{28}$$

Table 9 Correlation Coefficients for Critical Lane Flow Ratios and Ramp Flow Ratios

			Correlation significant?	
Relationship	Correlation coef.	Deg. of freedom	0.01 level	0.05 level
Pre-queue flow				
r_c vs. r_{on}	+0.607	11	no	yes
r_c vs. r_{off}	-0.554	11	no	yes
Queue discharge flow				
r_c vs. r_{on}	+0.785	11	yes	yes
r_c vs. r_{off}	-0.556	11	no	yes

and

$$r_{D,c} = 1.059 + 0.470r_{D,on} - 0.257r_{D,off} \quad (29)$$

where P and D in the subscripts refer to PQF and QDF respectively.

3.6 Capacity Models

One of the study objectives was to compare the performance of models that directly predict PQF and QDF with two-stage indirect models employing flow characteristics such as gaps and CLFRs as intervening variables. Section 3.5 documents relationships needed to construct models of both types. Equations 22 and 23 may serve as direct models linking PQF and QDF to population characteristics; Equations 24 and 25 give relationships between population characteristics and gaps; Equations 26 and 27 give relationships between population characteristics and CLFRs; and Equations 28 and 29 give relationships between ramp flows and CLFRs. Equations 24 through 29 may be combined with Equations 20 and 21 to produce two different indirect models each for PQF and QDF, one incorporating CLFRs estimated by Equation 26 or 27 and the other incorporating CLFRs estimated by Equation 28 or 29. This results in the following six candidate models, where P indicates models for estimating PQF and Q indicates models for estimating QDF:

Model P1:

$$\overline{q}_P = 2959 - 10.20\text{INC} - 88.96\text{YML} \quad (22)$$

Model P2:

$$\bar{q}_P = \frac{3{,}731 - 1{,}071.2\bar{g}_{P,c}}{r_{P,c}} \tag{30}$$

$$\bar{g}_{P,c} = 0.0912 + 0.0182\text{INC} + 0.0954\text{YML} \tag{23}$$

$$r_{P,c} = 1.165 + 0.0161\text{YML} - 0.00457\text{PCG} \tag{26}$$

or, substituting into Equation 18

$$\bar{q}_p = \frac{3{,}633 - 19.496\text{INC} - 102.171\text{YML}}{1.1652 + 0.0161\text{YML} - 0.00457\text{PCG}} \tag{31}$$

Model P3:

$$\bar{q}_P = \frac{3{,}731 - 1{,}071.2\bar{g}_{P,c}}{r_{P,c}} \tag{30}$$

$$\bar{g}_{P,c} = 0.0912 + 0.0182\text{INC} + 0.0954\text{YML} \tag{24}$$

$$r_{P,c} = 1.099 + 0.345 r_{P,\text{on}} - 0.302 r_{P,off} \tag{28}$$

or, combining the individual models

$$\bar{q}_p = \frac{3{,}633 + 19.496\text{INC} - 102.171\text{YML}}{1.099 + 0.345 r_{P,on} - 0.302 r_{P,off}} \tag{32}$$

Model Q1:

$$\bar{q}_D = 2806 - 10.93\text{INC} - 77.80\text{YML} \tag{23}$$

Model Q2:

$$\bar{q}_D = \frac{3{,}249 - 831.1\bar{g}_{D,c}}{r_{D,c}} \tag{33}$$

$$\bar{g}_{D,c} = 0.2486 + 0.0169\text{INC} + 0.0816\text{YML} \tag{25}$$

$$r_{D,c} = 1.013 + 0.0186\text{YML} - 0.00093\text{PCG} \tag{27}$$

or, combining the individual models

$$\overline{q}_D = \frac{3{,}042 - 14.553\text{INC} - 67.818\text{YML}}{1.013 + 0.0186\text{YML} - 0.00093\text{PCG}} \tag{34}$$

Model Q3:

$$\overline{q}_D = \frac{3{,}249 - 831.1\overline{g}_{D,c}}{r_{D,c}} \tag{33}$$

$$\overline{g}_{D,c} = 0.2486 + 0.0169\text{INC} + 0.0816\text{YML} \tag{25}$$

$$r_{D,c} = 1.059 + 0.470 r_{D,on} - 0.257 r_{D,off} \tag{29}$$

or, combining the individual models,

$$\overline{q}_D = \frac{3{,}042 - 14.553\text{INC} - 67.818\text{YML}}{1.059 + 0.470 r_{D,on} - 0.257 r_{D,off}} \tag{35}$$

These candidate models were evaluated by comparing them with one another, estimated capacities calculated using HCM methods, and the measured average values of PQF and QDF for the sites. Two comparisons were made: one for the sites used to develop the models and another for the six verification sites in San Diego. In each case, comparisons included calculating the error in the predicted capacity at each site for each model (including the HCM method), calculating the average error for all sites (to reveal any overall biases in the estimates), calculating the standard deviation of the measured and estimated flows (to give an idea of how the variation in the estimated flows for the different sites compared with that in the measured flows), and calculating correlation coefficients for estimated flows versus measured flows to determine how much of the variance of the measured flows was explained by each model. Models P3 and Q3 were not evaluated for the verification sites because the necessary data on ramp flows were not available at one site (SD-09) and the ramp configuration at another (SD-02) did not match that used in developing the model. With these two sites excluded, there would have been only four sites and only two degrees of freedom in the evaluation of the correlations.

Tables 10 through 14 present the results. Tables 10 and 11 summarize the measured and estimated flows for PQF and QDF respectively. Note that the HCM estimates are identical, since the HCM does not distinguish these flow conditions. Tables 12 and 13 give the estimation errors for the different models for individual sites, expressed as estimated flow minus measured flow. Table 12 summarizes this information for PQF and Table 13 summarizes it for QDF. Table 14 summarizes correlation coefficients for flow as estimated by each model and the corresponding measured flow.

The process of calibrating the models ensures that their overall bias will be close to zero when estimated flows are compared with those used to calibrate the model. This should be strictly true for Models P1 and Q1, for which the measured flow was used as the

Table 10 Results for Pre-Queue Flow Models

Site	Period	Measured PQF	Estimated PQF			
			Model P1	Model P2	Model P3	HCM
<u>Analysis sites</u>						
MN-02	2000	2153	2102	2108	2062	2236
	2004	1999	2102	2108	2045	2236
MN-08	2004	2041	2008	2081	2116	2249
MN-14	2000	1824	1797	1818	1750	2264
	2004	1686	1797	1818	1833	2264
MN-18	2000	2043	2063	2077		2197
MN-21	2000	2016	2091	2053	2073	2215
MN-22	2000	2047	2091	2053	2065	2201
MN-23	2000	2173	2032	2068	2122	2229
	2000	2059	2032	2068	2134	2229
MN-25	2000	2130	2066	2066	2007	2194
SD-05	2004	2095	2160	2102		2240
SD-07	2004	2108	2091	2021		2248
SD-08	2004	2179	2047	2048		2248
WA-01	2004	2097	2060	2117	2007	2283
WA-02	2004	2055	2059	2024	2166	2254
WA-03	2004	2120	2043	1968	2064	2239
WA-04	2004	2064	2112	2117		2064
<u>Verification sites</u>						
SD-01	2004	2419	2091	2021		2248
SD-02	2004	2416	2109	2017		2246
SD-03	2004	2179	2127	2257		2275
SD-06	2004	1982	2127	2257		2289
SD-09	2004	2287	2148	2094		2266
SD-12	2004	2160	2078	2022		2178

dependent variable in the regression, and approximately true for the two-stage models. Tables 12 and 13 verify that this is the case. In contrast, the current HCM method seriously overestimates both PQF and QDF for these sites: the average error is +189 veh/h/lane for PQF and +309 veh/h/lane for QDF, and both PQF and QDF are overestimated for every individual site.

For the verification sites, some overall bias is to be expected for all the models, and the size of this bias is an important test of their relative performance. In the case of PQF, the models developed by this study tend to underestimate the actual flows. The average error for model P1 is -127 veh/h/lane and that for P2 is -129 veh/h/lane. In this case, the HCM method leads to an average error of +10 veh/h/lane, which is much less than that of either of the other models. In the case of QDF, the models developed here still underestimate on

Table 11 Results for Queue Discharge Flow Models

Site	Period	Measured QDF	Estimated QDF			
			Model Q1	Model Q2	Model Q3	HCM
Analysis sites						
MN-02	2000	2033	1959	1971	1941	2236
	2004	1920	1959	1971	1919	2236
MN-08	2004	1936	1919	1916	2006	2249
MN-14	2000	1745	1740	1713	1656	2264
	2004	1647	1740	1713	1760	2264
MN-18	2000	1916	1907	1920		2197
MN-21	2000	1842	1965	1961	1935	2215
MN-22	2000	1884	1965	1961	1923	2201
MN-23	2000	2046	1934	1929	1994	2229
	2000	2022	1934	1929	2007	2229
MN-25	2000	1940	1913	1923	1903	2194
SD-05	2004	1989	2040	2034		2240
SD-07	2004	2043	1963	1953		2248
SD-08	2004	2083	2054	2063		2248
WA-01	2004	1986	1916	1933	1882	2283
WA-02	2004	1983	1923	1920	2018	2254
WA-03	2004	1966	1924	1906	1945	2239
WA-04	2004	1746	1973	1984		2064
Verification sites						
SD-01	2004	2175	1963	1953		2248
SD-02	2004	2184	1982	1968		2246
SD-03	2004	1926	1972	2014		2275
SD-06	2004	1824	1972	2014		2289
SD-09	2004	2094	2025	2021		2266
SD-12	2004	1965	1965	1950		2178

the average, but by a lesser amount (-48 veh/h/lane for model Q1 and -41 veh/h/lane for model Q2), and the HCM method leads to a large overestimate (+222 veh/h/lane).

The correlation between estimated and measured flows is an indicator of a model's ability to explain the variation in flows from site to site. A model that explains all such variation perfectly will have a correlation coefficient of +1.000 and a model that explains none of the variation will have a correlation coefficient of zero. Significant positive correlations exist for all of the models developed here when predicted flows are compared with the data used to calibrate the models. These correlation coefficients are +0.838 for model P1, +0.811 for model P2, +0.767 for model P3, +0.672 for model Q1, +0.670 for model Q2, and +0.797 for model Q3, all of which are significant at the 0.01 level. Correlation coefficients for the HCM method, on the other hand, are near-zero for

Table 12 Pre-queue Flow Model Errors

		Error, estimated flow – measured flow			
Site	Period	Model P1	Model P2	Model P3	HCM
Analysis sites					
MN-02	2000	-51	-46	-91	+82
	2004	+103	+109	+46	+237
MN-08	2004	-32	+40	+75	+209
MN-14	2000	-27	-6	-75	+439
	2004	+111	+132	+147	+578
MN-18	2000	+19	+34		+154
MN-21	2000	+75	+37	+57	+199
MN-22	2000	+44	+6	+17	+153
MN-23	2000	-141	-105	-51	+56
	2000	-27	+10	+76	+170
MN-25	2000	-64	-64	-123	+63
SD-05	2004	+65	+6		+145
SD-07	2004	-17	-86		+140
SD-08	2004	-8	+5		+81
WA-01	2004	-37	+20	-91	+186
WA-02	2004	+4	-31	+111	+199
WA-03	2004	-76	-151	-56	+119
WA-04	2004	+48	+53		+194
Average error		-1	-2	+3	+189
Verification sites					
SD-01	2004	-328	-398		-171
SD-02	2004	-307	-399		-171
SD-03	2004	-52	-78		+96
SD-06	2004	145	+275		+307
SD-09	2004	-139	-193		-21
SD-12	2004	-82	-138		+18
Average error		-127	-129		+10

both PQF and QDF. In the case of the verification sites, however, all correlation coefficients are negative and none is significant at the 0.05 level. This indicates that none of the models considered – that is, the models developed by this study and the current HCM methods – is able to explain the variation in flows at the verification sites.

A final point of comparison for the different models is the maximum errors in estimated flows at individual sites. For PQF at the sites used to develop the models, these are -141 veh/lane for model P1, -151 veh/h/lane for model P2, +147 veh/h/lane for model P3, and

Table 13 Queue Discharge Flow Model Errors

		Error, estimated flow – measured flow			
Site	Period	Model Q1	Model Q2	Model Q3	HCM
Analysis sites					
MN-02	2000	-74	-62	-92	+202
	2004	+39	+51	-1	+316
MN-08	2004	-18	-20	+70	+313
MN-14	2000	-4	-32	-89	+519
	2004	+93	+66	+113	+616
MN-18	2000	-9	+5		+282
MN-21	2000	+124	+119	+94	+373
MN-22	2000	+81	+77	+39	+317
MN-23	2000	-113	-117	-52	+183
	2000	-88	-93	-15	+207
MN-25	2000	-27	-16	-36	+254
SD-05	2004	+51	+46		+252
SD-07	2004	-80	-90		+205
SD-08	2004	-30	-21		+165
WA-01	2004	-70	-53	-104	+297
WA-02	2004	-60	-63	+35	+271
WA-03	2004	-42	-60	-21	+273
WA-04	2004	+227	+238		+513
Average error		0	-1	-5	+309
Verification sites					
SD-01	2004	-212	-222		+73
SD-02	2004	-202	-216		+62
SD-03	2004	+46	+88		+349
SD-06	2004	+148	+190		+465
SD-09	2004	-69	-73		+172
SD-12	2004	0	-15		+213
Average error		-48	-41		+222

+578 veh/h/lane for the HCM method. For QDF at these sites, they are +227 veh/h/lane for model Q1, +238 veh/h/lane for model Q2, +113 veh/h/lane for model Q3, and +616 veh/h/lane for the HCM method. For PQF at the verification sites, the maximum errors are -328 veh/h/lane for model P1, -399 veh/h/lane for model P2, and +307 veh/h/lane for the HCM method. For QDF at these sites they are -212 veh/h/lane for model Q1, -222 veh/h/lane for model Q2, and +465 veh/h/lane for the HCM method. In relative terms, maximum errors for individual sites used to develop the models amount to about 5 to 10 percent of the measured flow and, at the verification sites, to about 10 to 15 percent.

Table 14 Correlation Coefficients, Measured Flows vs. Estimated Flows

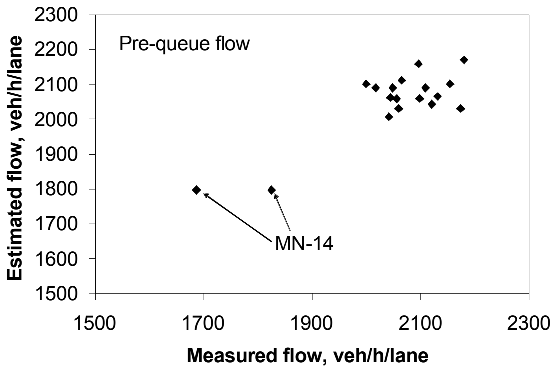
			Correlation significant?	
Relationship	Correlation coef.	Deg. of freedom	0.01 level	0.05 level
Analysis sites				
PQF vs. P1	+0.838	16	yes	yes
PQF vs. P2	+0.811	16	yes	yes
PQF vs. P3	+0.767	11	yes	yes
PQF vs. HCM	-0.288	16	no	no
QDF vs. Q1	+0.672	16	yes	yes
QDF vs. Q2	+0.670	16	yes	yes
QDF vs. Q3	+0.797	11	yes	yes
QDF vs. HCM	-0.159	16	no	no
Verification sites				
PQF vs. P1	-0.215	4	no	no
PQF vs. P2	-0.743	4	no	no
PQF vs. HCM	-0.192	4	no	no
QDF vs. Q1	-0.256	4	no	no
QDF vs. Q2	-0.482	4	no	no
QDF vs. HCM	-0.211	4	no	no

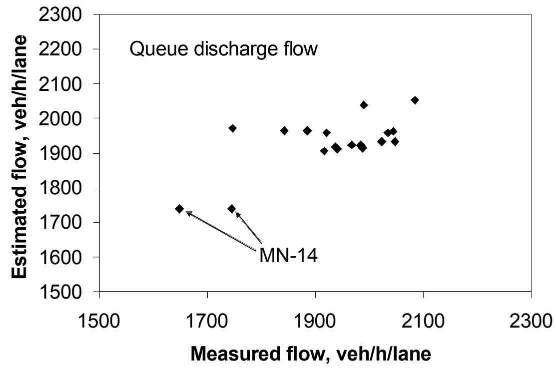
Maximum errors in flows for individual sites estimated by the HCM method exceeded those for the other methods (except in the case of PQF at the verification sites, where they were roughly equal) and in the worst case amounted to about 37 percent of the measured flow.

3.7 Revised Capacity Models

One possible reason for the evident lack of transferability of the models discussed in the preceding section (that is, their inability to explain variations in flow at the verification sites) is that they may have been distorted by data from anomalous sites. Figure 6 shows scatter plots of estimated and measured flows for models P1 and Q1 for the sites used for calibration. From these plots, it is clear that in each case there are two points in the lower left-hand corner that are separated from the other data and that evidently had considerable influence on the models. These points are associated with site MN-14, which is unusual in at least two respects: first, it had the lowest PQF and QDF recorded at any of the sites and, second, its commuter shed zone has by far the highest percentage of males aged of 18 and 24 years (see Tables B1, B2, and C3). This latter feature is largely a result of the fact that the zone includes student housing at the University of Minnesota. Since there is no real reason to believe that University of Minnesota students were disproportionately present in the evening peak traffic stream at this site, it is likely that the connection between the low flow and the high percentage of young males is a coincidence. If so, it is

Figure 6 Scatter Plots, Estimated vs. Measured Flows for Sites Used in the Calibration of Models P1 and Q1





possible that data from these sites distorted the predictive models by exaggerating the importance of the presence of young males. To explore this possibility, the stepwise regression analysis was repeated for the single-stage models of PQF and QDF with the MN-14 data omitted. The result was that the only significant explanatory variable was the number of lanes. The resulting single-stage models (designated P4 and Q4) are as follows:

Model P4

$$\overline{q}_P = 2{,}000 + 32.27\text{LNS} \tag{36}$$

Model Q4

$$\overline{q}_D = 1{,}775 + 68.23\text{LNS} \tag{37}$$

Table 15 gives the resulting estimates of PQF and QDF for two-lane, three-lane, and four-lane sites, as well as the means and standard deviations of measured flows for the sites used for calibration. It shows that the estimates produced by models P4 and Q4 are similar to the mean measured flows for sites with the corresponding number of lanes. Correlation coefficients for estimated flow versus measured flow for the sites used in calibrating the models are +0.469 for model P4 and +0.629 for model Q4. The correlation for model P4 is not significant at the 0.05 level, but that for model Q4 is significant at the 0.01 level.

All but one of the verification sites had 4 lanes. For these sites, the mean PQF was 2,257 veh/h/lane and the mean QDF was 2,041 veh/h/lane. On the average, Model P4 underestimated measured PQF, but Q4 slightly overestimated QDF. This result is largely explained by the fact that mean PQF for the verification sites was about 6 percent above that for the sites used to calibrate the model, while mean of QDF was nearly equal for both groups of sites. Since all but one of the verification sites had the same number of lanes, models P4 and Q4 obviously cannot explain the variation in flow among them.

Table 15 Estimated and Measured Flows for Sites with Different Numbers of Lanes

Measure	Number of lanes		
	2	3	4
Pre-queue flow			
Model P4	2065	2097	2129
Mean PQF	2064	2098	2127
St. dev., PQF	53.1	52.3	45.2
Queue discharge flow			
Model Q4	1911	1980	2048
Mean QDF	1908	1991	2038
St. dev., QDF	87.7	43.6	47.5

The conclusion that the number of lanes is the only significant explanatory variable for PQF and QDF suggests that regression models may not be the best approach to the prediction of capacity flows. The number of lanes is a discrete variable, and the relationships between it and PQF and QDF may not be exactly linear. Consequently, a simpler (and possibly more accurate) approach is to use the mean value of PQF and QDF for sites with a particular number of lanes as the predicted flow for sites with a similar number of lanes and to use the standard deviation of the site-mean flows as an indicator of the precision of the estimate. Table 15 gives the means and standard deviations for the sites used in calibrating the models. In the case of four-lane sites, however, inclusion of data from the verification sites may result in a more useful estimate. If the verification sites are included, the mean PQF for such sites is 2,208 veh/h/lane with a standard deviation of 155.6 veh/h/lane and mean QDF is 2,040 veh/h/lane with a standard deviation of 123.1 veh/h/lane.

4. DISCUSSION

4.1 Results and Models

Section 1.3 outlined an alternative to the current approach to bottleneck capacity analysis and presented a number of hypotheses about relationships among flow characteristics and site characteristics. In light of the results of the research, these hypotheses may be evaluated as follows:

Gaps will be related negatively to the proportions of young people, males, and wealthy people in the traffic stream. The results do not support this hypothesis. When data from site MN-14 were included in the analysis, there were significant *positive* relationships between gaps and median income and between gaps and the percentage of males aged 18 to 24. When data from this site were omitted, there was no significant relationship between gaps and percent of males aged 18 to 24; however, there was a significant positive univariate correlation between median income and gaps.

CLFR will be related positively to the proportions of young people, males, and wealthy people in the driver population. This hypothesis was partially verified. When data from site MN-14 were included, there was a significant positive relationship between CLFR and the percentage of males aged 18 to 24. There was no significant relationship between median income and CLFR. When data from site MN-14 were omitted, there was no significant relationship between either of these variables and CLFR.

CLFR and gaps will be negatively correlated. The results do not support this hypothesis. No significant correlation between CLFR and gaps was found for either PQF or QDF.

Gaps will be related negatively to metropolitan area population and the population density in the vicinity of the site. To the extent that this hypothesis could be tested, the results did not support it. Since there were only three metropolitan areas involved and they are of roughly similar size, it was not possible to test the part of the hypothesis related to metropolitan area size. There was no significant relationship between gaps and the population density in the vicinity of the sites.

CLFR will be related positively to metropolitan area population and population density in the vicinity of the site. To the extent that this hypothesis could be tested, the results did not support it. Since there were only three metropolitan areas involved and they are of roughly similar size, it was not possible to test the part of the hypothesis related to metropolitan area size. There was no significant relationship between CLFR and the population density in the vicinity of the sites.

Gaps will be smaller during work trip peaks than at other times of day. Although the study considered only work trip peak periods, the fact that queue discharge tended to be greatest early in the morning peak and late in the evening peak may lend some support to this hypothesis. In the three cases for which the time series of the gaps was also available, low gaps tended to correspond to high QDF. Variations over time in the interrelationships among gaps, flow ratios, and QDF do not appear to be simple, however.

Gaps will be larger where there are complicated traffic situations (weaving, high levels of lane changing, closely-spaced ramps, left hand entrances or exits, etc.) than where traffic situations are simple. There was insufficient data to test this hypothesis fully, but to the extent it could be tested, it appears to be false. There were four sites that were either entrance or exit legs from weaving sections, but in general they did not have unusually large gaps. No data on lane-changing were available. There appeared to be no relationship between ramp spacing and gaps, and gaps at the one site with a left-hand exit were smaller than average.

Gaps will be related positively to roadway grade, especially in QDF. This hypothesis was not supported. There was no significant correlation between gap and roadway grade in either PQF or QDF. To some extent, this finding may result from the fact that the grades at the sites for which gaps could be computed were all relatively flat.

CLFR will be related positively to the proportion of heavy vehicles and the length and steepness of grade. This hypothesis was also not supported. There was no significant correlation between average CLFR and roadway grade in either PQF or QDF. Once again, this finding may result from the fact that grades were relatively flat.

CLFR in critical sections will be related negatively to the ratios of entering and exiting flow to overall flow. This hypothesis appears to be half true. For merge bottleneck sections with an on-ramp at the upstream end and an off-ramp at the downstream end, CLFR was found to be negatively correlated with the ratio of exiting flow but *positively* correlated with the ratio of entering flow. In all cases, these correlations were significant at the 0.05 level.

The study results tend to support the idea that gaps are the most important factor in determining capacity flows, with lane flow distributions playing a lesser, but important role. Although it remains plausible that gaps and flow distributions are the result of driver behavior, and that they are influenced by the characteristics of bottlenecks and the traffic using them, no satisfactory models for predicting either the intervening variables or the flows for pre-queue and queue discharge conditions could be discovered, and most of the hypotheses about the relationships between the intervening variables and the bottleneck site characteristics proved false.

It is possible, of course, that satisfactory models could be discovered if different commuter-shed zones had been used or different explanatory variables had been explored. This seems unlikely, however: there is no obvious reason to think that the populations of either larger or smaller zones would have been more representative of the actual driver populations or that other (and seemingly less plausible) explanatory variables would have succeeded. One obvious possibility is that the driver behavior that affects the flow characteristics is more a matter of individual psychology than socioeconomic characteristics.

The overall result is somewhat negative: it has been shown that the existing HCM methods fail to explain the variation in flow among sites and overestimate both PQF and QDF at the most of the sites studied, but no reliable models for predicting variations in capacity flows among sites could be identified. At best, mean PQF and QDF for sites with different numbers of lanes can be used to correct the biases in the HCM methods, and information about the standard deviations of mean flows can be used to quantify the uncertainty of predicted PQF and QDF.

4.2 Approach

The failure to identify reliable models of PQF and QDF raises obvious questions about the appropriateness of the proposed approach to analysis of bottleneck capacity. Key features of this approach were (*a*) separate consideration of PQF and QDF, (*b*) a focus on derived flow characteristics such as gaps and CLFR, and (*c*) a two-stage modeling process in which the flow characteristics were used as intervening variables to link site characteristics to PQF and QDF.

The results suggest that separate consideration of PQF and QDF is very important to the accurate prediction of bottleneck performance. Leaving aside the theoretical and philosophical issues involved in the definition of capacity, it is clear that the difference between average PQF and QDF at any given site can be quite large, so that any analysis that does not consider them separately is apt to lead to confusion and inaccurate representation of at least one of these states. In particular, "capacities" calculated by the current HCM methods seriously overstate QDF. Consequently, bottleneck capacities calculated by current HCM methods will lead to serious errors if used in simulations of congested flow.

The value of other features of the approach is less clear. The results of the research suggest that gaps are by far the most important behavioral influence on both PQF and QDF, and that CLFR is also important. These results are important for the insight they provide, since they reinforce the idea that variations in driver behavior are a critical influence on variations in bottleneck capacity; but because the variations in gaps and CLFR could not be explained in terms of population or site characteristics, this insight does little to improve practical capacity analysis.

Finally, in terms of the actual prediction of average PQF and QDF, there was very little difference in the performance of two-stage and one-stage models. Both reproduced the measured flows at the sites used for calibration about equally well and neither was able to satisfactorily explain the variation in flow at the verification sites. Both the HCM methods and the models developed as part of this study resulted in negative correlations when applied to the verification sites, suggesting that in both cases the models incorporate the wrong variables. Consequently, it appears that better selection of explanatory variables is more likely to improve the accuracy of bottleneck capacity predictions than is use of two-stage models.

4.3 Methodology and Data

Section 2 suggested that there are two general approaches to the study of traffic behavior at freeway bottlenecks: the intensive and the extensive. This study, like most past research related to freeway capacity, followed the extensive approach. In the absence of resource constraints, the ideal approach would be one that is both intensive and extensive: that is, one in which many bottlenecks are analyzed to determine the exact flow mechanisms involved in the performance of each and then compared with one another to explain variations in performance. In the absence of that level of information, it is likely that the extensive approach will continue to be used in research intended to support the practical analysis of highway capacity. Since that is the case, it is important to consider the advantages and limitations of this approach, especially as they were experienced in this project. Issues of particular concern are the adequacy of the sample of sites, the availability and quality of data, the validity of some of the underlying statistical assumptions, and the validity of the methods used to identify periods of PQF and QDF.

The distinguishing feature of the extensive approach is that it involves data samples that are “large” in terms of the number of sites considered and/or the number of days for which data are collected. In the case of this study the initial goals (selected somewhat arbitrarily) were to study at least 20 sites and to analyze data for at least 50 days at each site. Neither goal was fully met: once MN-14 was excluded, only 14 sites turned out to be suitable for use in developing the models and in several cases (most notably the data for the Minneapolis-St. Paul sites taken during the experimental shutdown of the ramp metering system in 2000) fewer than 50 days worth of data were available. Further, in several other cases, usable data were available for fewer than 50 days. The results of the study suggest that the goal of analyzing traffic data for 50 days at each site was probably excessive – 20 to 30 days would appear to be adequate to establish the distributions of the flow characteristics – but the number of sites and degree to which they were representative are major concerns.

One obvious limitation of the sample is that bottlenecks are of several types – merges, weaving sections, etc. – and these were not equally represented. Of the 14 sites used in the development of the model (again, excluding MN-14), eight were merge bottlenecks, three were exit legs from weaving sections, one was the entrance leg to a weaving section, one was a diverge, and one was a lane drop. Even in the case of the merge bottlenecks, the sample size is too small to provide much confidence that the results are representative, and this is certainly true for the other types. It is reasonable to suspect that bottleneck flow characteristics differ depending on the type of bottleneck; however, the study did not confirm this because the sample sizes were so small that it was impossible to tell.

A second sense in which the sample of sites may not have been representative is in terms of their geographical distribution. Not only were all of them from metropolitan areas of roughly similar size, but within those metropolitan areas, the sites tended to be clustered. For instance, four of the Minneapolis-St. Paul sites (MN-18, MN-21, MN-22, and MN-25) are on the same freeway within about 4 km of one another.

The limitations on the size and distribution of the sample of sites were largely the result of the availability and quality of automatically-collected traffic data. The growth in traffic surveillance systems in the recent past, coupled with increased use of the internet to distribute traffic data, has created the impression that a major new resource is available for conducting extensive studies related to traffic flow. To some extent, this impression is valid, but the reality is that there is less useful data available than might be thought.

In the first place, detailed traffic data is still most readily available from a small number of well-established surveillance systems, such as the ones used here. Next, the existing data-collection systems were designed for a variety of functions, and in some cases the data available still reflect their original rationale; the most notable examples of this are the systems (such as the one in San Diego) that were originally intended to support traffic-responsive ramp metering and consequently have mainline detectors located only upstream of on-ramps. Finally (and perhaps most importantly), the resources available to maintain traffic surveillance systems are rarely adequate to keep them fully functional. As a result, individual detectors are often out of order for extended periods of time. The placement of detectors and the prevalence of long-term detector malfunctions were both serious constraints on the selection of study sites. The placement of detectors in San Diego (and elsewhere in California) tended to rule out use of California merge bottlenecks in the development of models; meanwhile, long-term detector malfunctions prevented use of a number of otherwise attractive sites in all the metropolitan areas.

Even where appropriate traffic data are available, there remain questions about their quality. Section 2.3.1 describes data screening procedures and the results of attempts to quantify possible biases in counts. Conclusions about the level of bias in the counts must remain tentative, since there are no independent counts available to establish "ground truth." One of the limitations of extensive studies is that they must of necessity rely on automatic counts, and the effort involved in conducting hand counts to verify these is prohibitive. On the basis of comparisons of counts at adjacent stations, however, the count biases appear to be on the order of zero to five percent; if the biases are indeed in that range, they are relatively small compared to other potential sources of error.

In the case of this study, a final concern about the traffic data is that the study results depend in part on the accuracy with which periods of PQF and QDF were identified. Since this was done visually, the process relied to some extent on the judgment of the analyst and may have been subject to some inconsistency or other inaccuracy. Since periods of QDF were far longer on the average than were periods of PQF, the estimates of PQF characteristics were more likely to be affected by errors in identifying the beginning and end of the flow periods than were those of QDF.

Although the availability and quality of traffic data do impose important limitations on extensive studies of freeway bottleneck capacity, the lack of readily-available data about site characteristics imposes far more serious ones. It was hypothesized at the beginning of this study that bottleneck flow characteristics are the result of the lane configurations and geometric characteristics of the sites, vehicle population characteristics, and driver population characteristics. In the case of urban freeways, current HCM methods emphasize the effect of lane configurations, geometric characteristics, and vehicle population characteristics; the alternative approach added driver population characteristics as a possible major influence.

One possible reason that the current HCM method focuses on configuration, geometric, and vehicle population characteristics is that it is relatively easy to quantify them. Even so, special data collection efforts are required to apply the HCM method, since the heavy vehicle counts routinely maintained by most state departments of transportation are not compatible with the HCM method – they are normally recorded as 24-hour counts rather than peak period counts, and they do not include a distinction between trucks and buses and recreational vehicles. Consequently, special hand counts – or guesswork – are required to apply the HCM method.

In the case of driver population characteristics, the situation is far worse. At present, there appear to be no sources of direct information about the characteristics of drivers traversing individual freeway segments. A potential source is travel-diary surveys routinely carried out by metropolitan planning organizations as a part of travel demand forecasting efforts; however, it appears that these surveys normally do not ask respondents about their routes (only their origins and destinations), so that it is not possible to isolate data for users of particular facilities. It might be possible to collect such data by means of special surveys that target the users of particular facilities; however, if models of flow characteristics were based on specially-collected socioeconomic data (as opposed to readily-available data such as that provided by the census), it might be difficult to use them in routine capacity analysis.

In the absence of direct information about driver population characteristics, this study relied on the characteristics of the general population as revealed by census data for somewhat arbitrarily defined “commuter sheds” related to the bottlenecks. This was obviously a rather crude expedient. In the first place, the census data do not provide information on some of the driver characteristics expected to be relevant, such as trip purpose. Next, there is no way to tell how the characteristics of the general population compare with those of the users of the freeway. Finally, the commuter sheds represent only a part of the area from which the users of the freeway might be coming, and there is no way to know how their population characteristics relate to those of the entire area contributing to the freeway flow. Given all this uncertainty, it is not surprising that this approach did not result in relationships that explain the variation in flow at the verification sites.

As previously stated, it is likely that the extensive approach will continue to be used in research intended to provide a basis for the practical highway capacity analysis. The limitations of this method are serious enough, however, to suggest that more attention should be paid to intensive studies of bottlenecks. Where the question is how to improve the operation of an existing bottleneck, the intensive approach is obviously to be preferred. Moreover, if intensive studies are carried out at enough bottlenecks, it may be possible to identify previously unsuspected physical features or traffic flow phenomena that affect bottleneck capacity. To give one example, how common is the flow mechanism reported by Rudjanakanoknad (2005), in which a drop in QDF was triggered by a particular concentration of traffic in a short segment of the right lane of a freeway? The intensive study of bottlenecks may be facilitated by developing a set of procedures for carrying out such studies and by establishing better traffic data collection systems in the vicinity of known bottlenecks.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Major conclusion may be summarized as follows:

1. Current HCM methods do not explain variations in capacity flows among relatively flat urban and suburban bottleneck sections. In addition, estimates based on the HCM methods are biased high for QDF at all sites (confirming that the “capacity” measured by the HCM is not QDF); at most sites, such estimates are also biased high for PQF.

2. Differences among sites in PQF and QDF are primarily the result of differences in gaps in the critical (most heavily traveled) lane. Differences in lane use distributions also contribute to differences in flow per lane but they are somewhat less important.

3. For relatively flat urban or suburban bottleneck sections, differences among sites in gaps and lane flow distributions are presumably the result of differences in the socioeconomic characteristics of the population contributing to the traffic stream, although the lane configuration may also have some influence. Site geometry (except the number of lanes) and vehicle population characteristics (to the extent they could be determined) do not appear to be significant influences. If results based on the inclusion of an apparently anomalous site are discounted, no specific relationships between socioeconomic characteristics and flow characteristics could be identified, however.

4. The performance of two-stage models using gaps and CLFR as intervening variables to link population characteristics to PQF and QDF is roughly the same as that of similar one-stage models.

5. For individual bottlenecks, there is substantial variation in flow from episode to episode of both PQF and QDF. Coefficients of variation for mean flow in different periods of PQF range from 0.02 to 0.08. For QDF the range is from 0.02 to 0.06.

6. Where periods of congestion are relatively long, there is some evidence that QDF varies with time of day, with the highest flows occurring early in the morning peak and late in the evening peak.

7. Lack of data and poor data quality remain major barriers to understanding variations in PQF and QDF among bottleneck sites. The most important deficiencies are lack of properly located traffic detectors, the prevalence of long-term detector failures, lack of detail in routinely-collected heavy vehicle presence data, and lack of data about the driver population and trip purpose characteristics of specific traffic streams.

5.2 Recommendations

Since the current HCM methods appear to overestimate capacities in most cases and do not distinguish between PQF and QDF, it is recommended that the results of this study be used to supplement bottleneck capacity analyses carried out with existing HCM methods.

For urban sites, Table 16 may be used to identify possible biases in the results of HCM analyses, to provide for separate estimates of PQF and QDF, and to quantify the uncertainty of capacity estimates. For freeways with 2, 3, and 4 directional lanes, the table shows (*a*) the range of PQF and QDF between one standard deviation below and one standard deviation above the mean and (*b*) the approximate range of the standard deviations of the mean flows for different episodes of PQF and QDF. For example, for a site with three directional lanes, there is approximately a two-thirds probability that mean QDF will fall between 1,954 and 2,035 veh/h/lane; furthermore, there is about a two-thirds probability that flows for individual episodes of QDF for such a site will fall within a range of 50 to 90 veh/h/lane above and below the mean for all such episodes at the site.

Table 16 Recommended Ranges for Pre-Queue and Queue Discharge Flow Estimates

Number of directional lanes	Flow range, veh/h/lane		Standard deviation of mean flows for individual episodes, veh/h/lane	
	PQF	QDF	PQF	QDF
2	2015 – 2120	1820 – 1995	90 – 150	50 – 105
3	2045 – 2150	1945 – 2035	75 – 110	50 – 90
4	2050 – 2365	1915 – 2165	70 – 170	35 – 80

Other recommendations include:

1. Caltrans should conduct or sponsor research to refine the values in Table 16 by measuring PQF and QDF for as many freeway bottlenecks in California as possible. Since the only data required are the total flow into or out of the bottleneck section, many more sites should be available than was the case for this study. A sample size of 20 to 30 days during which the bottleneck is active should be sufficient.

2. To facilitate this research, automated techniques for identifying periods of PQF and QDF should be developed. Availability of such techniques could greatly reduce the cost and tediousness of the traffic data reduction undertaken in this study, and would eliminate much of the concern about inconsistencies in the identification of the flow periods. Preliminary work undertaken as a follow-up to this study suggests it should be feasible to detect flow periods automatically; however, the details of the technique still need to be worked out.

3. Caltrans should consider upgrading freeway traffic surveillance systems to provide more and better data about conditions in and around bottleneck sections. This upgrade should include additional detector locations, particularly within the suspected bottleneck sections. A major barrier to doing this in the past has been the expense and disruption required to install loop detectors. Detector technology has now advanced to the point that Caltrans has accepted non-intrusive

microwave radar detectors as being functionally equivalent to loop detectors and has issued a standard for their installation (Wald, 2004). These sensors may be mounted on poles beside the roadway, with solar collectors and wireless data transmission systems used to provide power and download data. The availability of this technology should greatly reduce the cost and disruption involved in establishing additional permanent data collection stations. Also, Caltrans should strongly consider devoting more resources to the maintenance of existing traffic surveillance systems.

4. Researchers should continue to pursue the issue of whether flow characteristics such as gaps can be related to identifiable characteristics of the driver population. In order to provide direct data on the socioeconomic characteristics of drivers using specific freeway sections, Caltrans should request that metropolitan planning organizations in California include questions about routes in travel diary surveys. If this proves infeasible or if the sample sizes produced by area-wide surveys are too small to provide a reasonable estimate of the driver population characteristics for individual sites, Caltrans should consider conducting special surveys.

5. Caltrans should consider conducting or sponsoring intensive studies of as many bottlenecks as possible. Currently, a major barrier to conducting such studies is the difficulty of collecting data at many bottleneck sites. Establishment of enhanced traffic surveillance systems around bottlenecks, as recommended above, coupled with additional video surveillance in and around bottlenecks, would go a long way toward providing the necessary data collection capability. Failing this, research into portable automatic data collection systems that is now underway (PATH TO 6302) may result in data-collection systems that can be used on a temporary basis for intensive studies of bottlenecks.

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APPENDIX A

ASSUMED COMMUTER SHEDS FOR STUDY SITES

Site	County	Census tracts
MN-02	Hennepin	208.01, 208.04, 209.02, 215.01, 215.02, 215.03, 215.04, 215.05, 215.06, 265.08, 265.09, 265.10, 265.11, 265.12, 267.02, 267.10, 267.12, 267.13, 268.07, 268.16, 268.18
MN-08	Hennepin	33, 35.01, 35.02, 59.01, 59.02, 68, 73.01, 73.02, 77, 78.02, 79, 81, 82, 83, 84, 85, 95, 96, 107, 110, 1034, 1041, 1046, 1048, 1052, 1054, 1055, 1056, 1060, 1062, 1066, 1067, 1070, 1071, 1072, 1080, 1086, 1087, 1092, 1093, 1094, 1097, 1099, 1100, 1101, 1102, 1108
MN-14	Hennepin	27, 35.01, 59.01, 59.02, 68, 73.01, 73.02, 77, 78.01, 78.02, 79, 81, 82, 83, 84, 85, 218, 220, 228.01, 1028, 1029, 1034, 1041, 1046, 1047, 1048, 1049, 1050, 1052, 1054, 1055, 1056, 1057, 1060, 1064, 1065, 1066, 1069, 1071, 1072, 1075
MN-18	Hennepin	267.08, 267.10, 267.11, 267.12, 267.13, 267.14, 267.16, 269.07
MN-21	Anoka	511.02, 512.01, 512.02, 512.03, 512.06, 513.02, 513.04, 513.05, 514, 515.01, 515.02
	Hennepin	1.01, 1.02, 202, 203.01, 203.03, 203.04, 204, 206
	Ramsey	408.01, 408.02, 408.03, 411.03, 411.04, 411.05, 411.06, 412
MN-22	Anoka	511.02, 512.01, 512.02, 512.03, 512.06, 513.02, 513.04, 513.05, 514, 515.01, 515.02
	Hennepin	1.01, 1.02, 202, 203.01, 203.03, 203.04, 204, 206
	Ramsey	408.01, 408.02, 408.03, 411.03, 411.04, 411.05, 411.06, 412
MN-23	Ramsey	308, 309, 310, 312, 313, 314, 315, 320, 321, 322, 323, 324, 325, 326, 327, 328, 329, 330, 331, 332, 333, 334, 335, 336, 337, 338, 339, 340, 342, 344, 345, 349, 350, 351, 352, 353, 354, 355, 356, 357, 358, 359, 360
MN-25	Hennepin	267.08, 267.10, 267.11, 267.12, 267.13, 267.14, 267.16, 268.07, 268.08
SD-01	San Diego	200.24, 200.25, 201.05, 201.06, 201.07, 201.08, 201.09, 202.02, 202.12, 203.02, 203.04, 203.05, 203.07, 204.01, 204.03, 204.04, 204.05, 205, 206.02, 207.05, 207.07, 207.08, 207.09
SD-02	San Diego	32.01, 32.02, 32.04, 32.11, 32.12, 100.01, 100.03, 100.04, 100.05, 100.11, 117, 119.01, 120.01, 120.02, 120.03, 121.01, 121.02, 122, 123.03, 123.04, 128, 129, 131.02, 132.03, 132.04, 133.01, 133.03, 133.06, 133.07, 133.08, 133.12, 134.01, 134.09, 134.12, 134.13, 134.14
SD-03	San Diego	171.05, 174.01, 174.04, 175.01, 175.02, 176.01, 176.03, 177.01, 177.02, 178.05, 178.06, 178.08, 178.11, 178.12, 185.04, 198.03, 200.14
SD-05	San Diego	14, 15, 24.01, 25.01, 25.02, 30.01, 31.01, 31.09, 31.11, 31.13, 32.01, 32.02, 32.04, 33.01, 33.02, 33.03, 24.01, 34.03, 24.04, 42, 117, 118.02, 119.01, 119.02, 120.01, 120.02, 120.03, 121.01, 122, 123.02, 123.03, 123.04, 128, 129, 134.01, 134.09, 134.12, 134.13
SD-06	San Diego	171.05, 174.01, 174.04, 175.01, 175.02, 176.01, 176.03, 177.01, 177.02, 178.05, 178.06, 178.08, 178.11, 178.12, 185.04, 198.03, 200.14
SD-07	San Diego	200.24, 200.25, 201.05, 201.06, 201.07, 201.08, 201.09, 202.02, 202.12, 203.02, 203.04, 203.05, 203.07, 204.01, 204.03, 204.04, 204.05, 205, 206.02, 207.05, 207.07, 207.08, 207.09
SD-08	San Diego	8, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 21, 22.02, 24.01, 24.02, 25.01, 26.02, 27.09, 42, 43, 44, 83.45, 85.02, 85.04, 85.05, 85.06, 85.07, 85.09, 85.10, 85.11, 85.12, 85.13, 86, 87.01, 87.02, 88, 92.01, 92.02, 93.01, 93.04
SD-09	San Diego	98.02, 146.01, 148.01, 148.03, 149, 150, 152, 152, 153.01, 153.02, 154.03, 154.04, 156.01, 156.02, 157.01, 157.03, 157.04, 158.01, 158.02, 159.02, 160, 161, 162.01, 162.02, 163.01, 163.02, 164.01, 164.02, 165.01, 165.02, 166.16, 166.17, 167.01, 168.07, 168.09, 168.10
SD-12	San Diego	29.04, 29.05, 97.06, 98.02, 146.01, 147, 148.01, 148.03, 148.04, 149, 150, 151, 152, 153.01, 153.02, 154.03, 154.04, 156.01, 156.02, 157.01, 157.03, 157.04, 158.01, 158.02, 159.02, 160, 161, 162.01, 162.02, 163.01, 163.02, 164.01, 164.02, 165.01, 165.02, 166.16, 166.17, 167.01, 168.07
WA-01	King	218.03, 218.04, 219.03, 219.04, 219.05, 219.06, 220.01, 220.03, 220.05, 220.06, 221.02, 222.01, 222.02, 224, 225, 226.03, 226.05, 227.03, 323.19
	Snohomish	529.11, 519.16, 519.17, 519.18
WA-02	King	218.02, 218.03, 218.04
	Snohomish	417.02, 418.04, 418.06, 518.01, 518.02, 519.05, 519.09, 519.11, 519.15, 519.16, 519.17, 519.18, 519.19, 519.20, 520.03, 520.04
WA-03	Snohomish	416.05, 416.06, 417.01, 417.02, 418.04, 418.05, 418.06, 418.07, 418.08, 429.04, 419.05, 512, 514, 515, 517.01, 517.02, 518.01, 518.02, 519.05, 519.09, 520.04, 520.05
WA-04	King	247.01, 247.02, 250.01, 251.01, 252, 253, 254, 255, 256, 257.01, 257.02, 258.01, 258.03, 258.04

APPENDIX B

FLOW CHARATERISTICS OF STUDY SITES

Table B1 Pre-Queue Flows

Site	Dates	Mean, veh/h/lane	St. dev., veh/h/lane	Coefficient of variation	Mean duration, min	Number of periods
MN-02	10/16/00-12/1/00	2153	310	0.14	39.1	24
	6/1/04-8/27/04	1999	318	0.16	14.6	30
MN-08	6/1/04-8/27/04	2041	371	0.18	26.8	38
MN-14	10/16/00-12/1/00	1824	253	0.14	13.5	15
	6/1/04-8/27/04	1686	370	0.22	10.4	6
MN-18	10/16/00-12/1/00	2043	230	0.11	17.2	18
MN-21	10/16/00-12/1/00	2016	213	0.11	9.4	4
MN-22	10/16/00-12/1/00	2047	302	0.15	13.6	13
MN-23	10/16/00-12/1/00	2173	286	0.13	12.0	14
	6/1/04-8/27/04	2059	406	0.20	20.1	33
MN-25	10/16/00-12/1/00	2130	241	0.11	13.6	21
SD-01	6/1/04-8/27/04	2419	251	0.10	13.7	60
SD-02	6/1/04-8/27/04	2416	287	0.12	12.7	30
SD-03	6/1/04-8/27/04	2179	248	0.11	18.2	60
SD-05	6/1/04-8/27/04	2095	251	0.12	14.8	46
SD-06	6/1/04-8/27/04	1982	294	0.15	9.8	37
SD-07	6/1/04-8/27/04	2108	268	0.13	15.0	42
SD-08	6/1/04-8/27/04	2167	306	0.14	8.3	51
SD-09	6/1/04-8/27/04	2287	266	0.12	15.0	10
SD-12	9/24/04-1/31/05	2160	293	0.14	9.0	45
WA-01	5/26/04-8/27/04	2097	316	0.15	17.4	40
WA-02	5/26/04-8/27/04	2055	254	0.12	15.7	53
WA-03	5/26/04-8/27/04	2120	322	0.15	17.7	52
WA-04	5/26/04-8/27/04	2064	206	0.10	14.2	42

Table B2 Queue Discharge Flows

Site	Dates	Mean, veh/h/lane	St. dev., veh/h/lane	Coefficient of variation	Mean duration, min	Number of periods
MN-02	10/16/00-12/1/00	2037	220	0.11	157.2	29
	6/1/04-8/27/04	1920	229	0.12	71.4	52
MN-08	6/1/04-8/27/04	1936	286	0.15	136.3	69
MN-14	10/16/00-12/1/00	1745	190	0.11	74.2	32
	6/1/04-8/27/04	1647	289	0.18	57.6	15
MN-18	10/16/00-12/1/00	1916	168	0.09	112.7	24
MN-21	10/16/00-12/1/00	1842	170	0.09	47.4	11
MN-22	10/16/00-12/1/00	1884	194	0.10	113.4	19
MN-23	10/16/00-12/1/00	2046	202	0.10	98.2	25
	6/1/04-8/27/04	2022	320	0.16	74.9	48
MN-25	10/16/00-12/1/00	1940	194	0.10	76.2	26
SD-01	6/1/04-8/27/04	2175	358	0.16	160.6	65
SD-02	6/1/04-8/27/04	2184	196	0.09	33.7	80
SD-03	6/1/04-8/27/04	1926	259	0.13	200.2	65
SD-05	6/1/04-8/27/04	1989	188	0.09	60.8	67
SD-06	6/1/04-8/27/04	1824	298	0.16	117.9	99
SD-07	6/1/04-8/27/04	2043	144	0.07	216.5	64
SD-08	6/1/04-8/27/04	2083	174	0.08	197.8	72
SD-09	6/1/04-8/27/04	2094	255	0.12	44.2	12
SD-12	9/24/04-1/31/05	1965	260	0.13	98.2	59
WA-01	5/26/04-8/27/04	1986	195	0.10	144.3	78
WA-02	5/26/04-8/27/04	1983	172	0.09	130.3	80
WA-03	5/26/04-8/27/04	1966	217	0.11	84.0	92
WA-04	5/26/04-8/27/04	1746	185	0.11	158.4	62

Table B3   Flow Characteristics for Pre-Queue Flows

Site	Period	Mean flow	Critical lane time gap	Critical lane passage time	Critical lane flow ratio	n
MN-02	2000	2153	1.28	0.30	1.10	24
	2004	1999	1.43	0.31	1.09	30
MN-08	2004	2041	1.45	0.28	1.05	38
MN-14	2000	1824	1.46	0.29	1.18	15
	2004	1686	1.58	0.29	1.18	6
MN-18	2000	2043	1.44	0.33	1.03	18
MN-21	2000	2016	1.28	0.34	1.15	4
MN-22	2000	2047	1.38	0.25	1.15	13
MN-23	2000	2173	1.18	0.33	1.13	14
	2000	2059	1.15	0.44	1.15	33
MN-25	2000	2130	1.36	0.25	1.09	21
SD-05	2004	2095	1.13	0.29	1.24	46
SD-07	2004	2108	1.34	0.26	1.13	42
SD-08	2004	2179	1.22	0.33	1.12	51
WA-01	2004	2097	1.45	0.29	1.04	40
WA-02	2004	2055	1.50	0.31	1.03	53
WA-03	2004	2120	1.44	0.24	1.07	52
WA-04	2004	2064	1.37	0.26	1.10	42

Table B4 Flow Characteristics for Queue Discharge Flow

Site	Period	Mean flow	Critical lane time gap	Critical lane passage time	Critical lane flow ratio	n
MN-02	2000	2037	1.35	0.38	1.05	29
	2004	1920	1.41	0.42	1.05	52
MN-08	2004	1936	1.47	0.32	1.07	69
MN-14	2000	1745	1.42	0.35	1.20	32
	2004	1647	1.59	0.32	1.18	15
MN-18	2000	1916	1.50	0.41	1.01	24
MN-21	2000	1842	1.41	0.42	1.10	11
MN-22	2000	1884	1.43	0.40	1.08	19
MN-23	2000	2046	1.24	0.41	1.09	25
	2004	2022	1.15	0.53	1.10	48
MN-25	2000	1940	1.46	0.32	1.08	26
SD-05	2004	1989	1.26	0.39	1.12	67
SD-07	2004	2043	1.35	0.33	1.07	64
SD-08	2004	2085	1.15	0.43	1.12	72
WA-01	2004	1986	1.36	0.37	1.08	78
WA-02	2004	1983	1.48	0.38	1.01	80
WA-03	2004	1966	1.46	0.30	1.07	92
WA-04	2004	1747	1.46	0.45	1.12	62

Table B5 Ramp Flows as a Percentage of Total Flow for Merge Bottlenecks

		PQF		QDF	
Site	Period	Pct. on-ramp flow	Pct. off-ramp flow	Pct. on-ramp flow	Pct. off-ramp flow
MN-02	2000	8.1	8.0	7.3	7.3
MN-02	2004	9.1	7.5	9.6	6.8
MN-08	2004	4.7	5.5	5.2	5.8
MN-14	2000	32.7	4.5	34.1	4.2
MN-14	2004	20.6	6.3	20.0	6.3
MN-21	2000	15.7	8.3	12.4	7.4
MN-22	2000	15.0	9.9	14.3	8.1
MN-23	2000	9.7	13.2	9.3	10.8
MN-23	2004	8.6	12.2	8.5	11.9
MN-25	2000	8.0	16.2	6.3	12.5
WA-01	2004	14.3	16.9	13.4	16.2
WA-02	2004	10.2	32.0	11.2	35.7
WA-03	2004	11.8	10.3	9.2	10.3

Table B6 Comparison of Pre-Queue Flows with Queue Discharge Flows

Site	Period	PQF	QDF	Difference, QDF – PQF	Difference, pct. of PQF	*t*	Deg. of freedom	Level of sig.
MN-02	2000	2153	2037	-116	-5.3	19.92	10988	3.3×10^{-87}
	2004	1999	1920	-79	-4.0	9.15	8299	3.6×10^{-20}
MN-08	2004	2041	1936	-105	-5.1	15.16	20846	6.3×10^{-52}
MN-14	2000	1824	1745	-79	-4.3	7.85	5147	2.4×10^{-15}
	2004	1686	1647	-39	-2.3	1.42	1851	0.078
MN-18	2000	2043	1916	-127	-6.2	17.13	6025	1.3×10^{-64}
MN-21	2000	2016	1842	-174	-8.6	8.42	1116	5.8×10^{-17}
MN-22	2000	2047	1884	-163	-8.0	14.45	4781	1.2×10^{-46}
MN-23	2000	2173	2046	-127	-5.8	10.76	5413	4.7×10^{-27}
	2004	2059	2022	-37	-1.8	3.69	8517	1.1×10^{-4}
MN-25	2000	2130	1940	-190	-8.9	21.29	4528	3.4×10^{-96}
SD-01	2004	2419	2175	-244	-10.1	27.10	22528	1.5×10^{-159}
SD-02	2004	2416	2184	-232	-9.6	28.7	6145	4.4×10^{-170}
SD-03	2004	2129	1926	-203	-9.5	44.17	28211	0
SD-05	2004	2095	1989	-106	-5.1	18.65	9542	1.3×10^{-76}
SD-06	2004	1982	1824	-158	-8.0	14.08	24068	4.0×10^{-45}
SD-07	2004	2108	2043	-65	-3.1	14.85	28965	4.9×10^{-50}
SD-08	2004	2167	2083	-84	-3.9	14.79	28742	1.2×10^{-49}
SD-09	2004	2287	2094	-193	-8.4	11.44	1358	2.6×10^{-29}
SD-12	2004-05	2160	1965	-195	-9.0	20.40	12388	2.8×10^{-91}
WA-01	2004	2097	1986	-111	-5.3	24.13	35449	6.0×10^{-128}
WA-02	2004	2055	1983	-72	-3.5	19.25	33771	1.9×10^{-82}
WA-03	2004	2120	1966	-154	-7.3	33.12	25938	6.3×10^{-236}
WA-04	2004	2064	1746	-318	-15.4	70.32	32547	0

Table B7 Results of Analysis of Variance for Individual Episodes of Pre-Queue Flow

			Degrees of freedom		
Site	Year	F	$P-1$	$N-p$	Level of significance
MN-02	2000	6.26	23	1851	1.2×10^{-18}
	2004	4.17	29	845	3.5×10^{-12}
MN-08	2004	2.74	37	2000	1.1×10^{-7}
MN-14	2000	3.56	14	390	1.5×10^{-5}
	2004	0.69	5	119	0.63
MN-18	2000	11.28	17	601	5.6×10^{-27}
MN-21	2000	7.61	3	71	0.0002
MN-22	2000	7.77	12	340	8.7×10^{-13}
MN-23	2000	2.79	13	321	0.0001
	2004	1.26	32	1295	0.16
MN-25	2000	7.88	20	549	3.7×10^{-20}
SD-01	2004	4.08	59	1586	1.1×10^{-21}
SD-02	2004	3.04	29	729	2.4×10^{-7}
SD-03	2004	3.13	59	2128	4.5×10^{-8}
SD-05	2004	1.97	45	1370	0.0002
SD-06	2004	2.12	36	691	0.0002
SD-07	2004	3.18	41	1219	1.4×10^{-10}
SD-08	2004	7.90	50	798	5.7×10^{-43}
SD-09	2004	0.60	9	290	0.80
SD-12	2004	1.91	44	763	0.0004
WA-01	2004	3.62	39	2052	6.3×10^{-13}
WA-02	2004	6.35	52	2444	6.2×10^{-39}
WA-03	2004	3.19	51	2715	4.6×10^{-13}
WA-04	2004	9.37	41	1745	7.1×10^{-51}

Table B8 Results of Analysis of Variance for Individual Episodes of Queue Discharge Flow

Site	Year	F	Degrees of freedom $P-1$	$N-p$	Level of significance
MN-02	2000	23.24	28	9086	1.0×10^{-114}
	2004	9.38	51	7374	3.8×10^{-68}
MN-08	2004	14.08	68	18741	1.2×10^{-152}
MN-14	2000	10.09	31	4712	1.5×10^{-46}
	2004	7.54	13	1549	1.3×10^{-14}
MN-18	2000	44.34	23	5384	6.1×10^{-183}
MN-21	2000	31.71	10	1032	8.4×10^{-54}
MN-22	2000	87.54	18	4291	1.1×10^{-274}
MN-23	2000	36.05	24	5055	1.7×10^{-153}
	2004	3.89	47	7143	1.2×10^{-17}
MN-25	2000	34.48	25	3934	8.5×10^{-149}
SD-01	2004	295.50	64	20819	0
SD-02	2004	10.21	79	5308	3.5×10^{-111}
SD-03	2004	8.92	64	25960	2.0×10^{-81}
SD-05	2004	13.18	66	8061	2.1×10^{-132}
SD-06	2004	8.89	98	23243	1.8×10^{-121}
SD-07	2004	23.46	63	27642	9.7×10^{-260}
SD-08	2004	18.24	71	28410	1.2×10^{-218}
SD-09	2004	8.88	11	1048	3.0×10^{-15}
SD-12	2004	5.71	58	11523	3.4×10^{-39}
WA-01	2004	30.00	76	33248	0
WA-02	2004	39.34	79	31196	0
WA-03	2004	15.90	91	23081	1.5×10^{-235}
WA-04	2004	55.00	61	29856	0

Table B9 Summary of Results of t-tests, Flows at Minnesota Sites, 2000 and 2004

Site	Year	$\bar{x}$	s	n	t	Level of sig., one tailed
<u>Pre-queue</u>						
MN_BN02	2000	2153	310	1875		
MN_BN02	2004	1999	318	875	12.80	0
MN_BN14	2000	1824	253	405		
MN_BN14	2004	1686	370	125	4.74	0
MN_BN23	2000	2173	286	335		
MN_BN23	2004	2059	406	1328	4.85	0
<u>Queue discharge</u>						
MN_BN02	2000	2037	220	9115		
MN_BN02	2004	1920	229	7426	33.33	0
MN_BN14	2000	1745	190	4744		
MN_BN14	2004	1647	289	1563	15.23	0
MN_BN23	2000	2046	202	5080		
MN_BN23	2004	2022	320	7191	4.83	0

Table B10 Means, Standard Deviations and Coefficients of Variation for Mean Flows during Episodes of Pre-Queue Flow and Queue Discharge Flow

		PQF			QDF		
Site	Dates	Mean	St. dev.	C.o.v	Mean	St. dev.	C.o.v
MN-02	2000	2162	96	0.04	2045	65	0.03
	2004	2018	94	0.05	1928	79	0.04
MN-08	2004	2046	81	0.04	1934	86	0.04
MN-14	2000	1833	97	0.05	1758	64	0.04
	2004	1709	70	0.04	1655	81	0.05
MN-18	2000	2057	150	0.07	1939	74	0.04
MN-21	2000	2035	140	0.07	1858	82	0.04
MN-22	2000	2063	155	0.08	1883	105	0.06
MN-23	2000	2173	107	0.05	2066	86	0.04
	2004	2063	75	0.04	2030	62	0.03
MN-25	2000	2142	115	0.05	1953	91	0.05
SD-01	2004	2422	95	0.04	2181	53	0.02
SD-02	2004	2425	94	0.04	2182	75	0.03
SD-03	2004	2181	70	0.03	1930	44	0.02
SD-05	2004	2100	78	0.04	2001	65	0.03
SD-06	2004	2001	104	0.05	1820	70	0.04
SD-07	2004	2111	81	0.04	2041	35	0.02
SD-08	2004	2199	168	0.08	2083	45	0.02
SD-09	2004	2280	40	0.02	2103	78	0.04
SD-12	2004-05	2174	110	0.05	1957	55	0.03
WA-01	2004	2095	86	0.04	1992	52	0.03
WA-02	2004	2067	91	0.04	1981	52	0.03
WA-03	2004	2111	93	0.04	1972	60	0.03
WA-04	2004	2056	101	0.05	1762	88	0.05

APPENDIX C

TIME OF DAY VARAITIONS IN QUEUE DISCHARGE FLOW

Time-of-day variations in QDF were investigated for five sites with especially long congested periods. At these sites, QDF from different days were averaged by time of day. In calculating these average flows, data for a particular day were included if there was QDF during any part of the 30-minute interval. As a result, some of the daily average flows used to calculate the overall averages were for less than 30 minutes. Consequently, sample sizes for average flows at each site vary depending on the 30-minute interval. Figures C1 through C5 are plots of average QDF by time of day; where data were available, the plots also show time-of-day averages of the CLFR and the gap. To make the plots of flow comparable to those of flow ratios and gaps, all measures have been normalized by dividing the 30-minute average value by the overall average. Also, to facilitate comparison of trends at different sites, all plots have the same vertical scale.

Figure C1 Variation of Queue Discharge Flow by Time of Day at Site SD-01

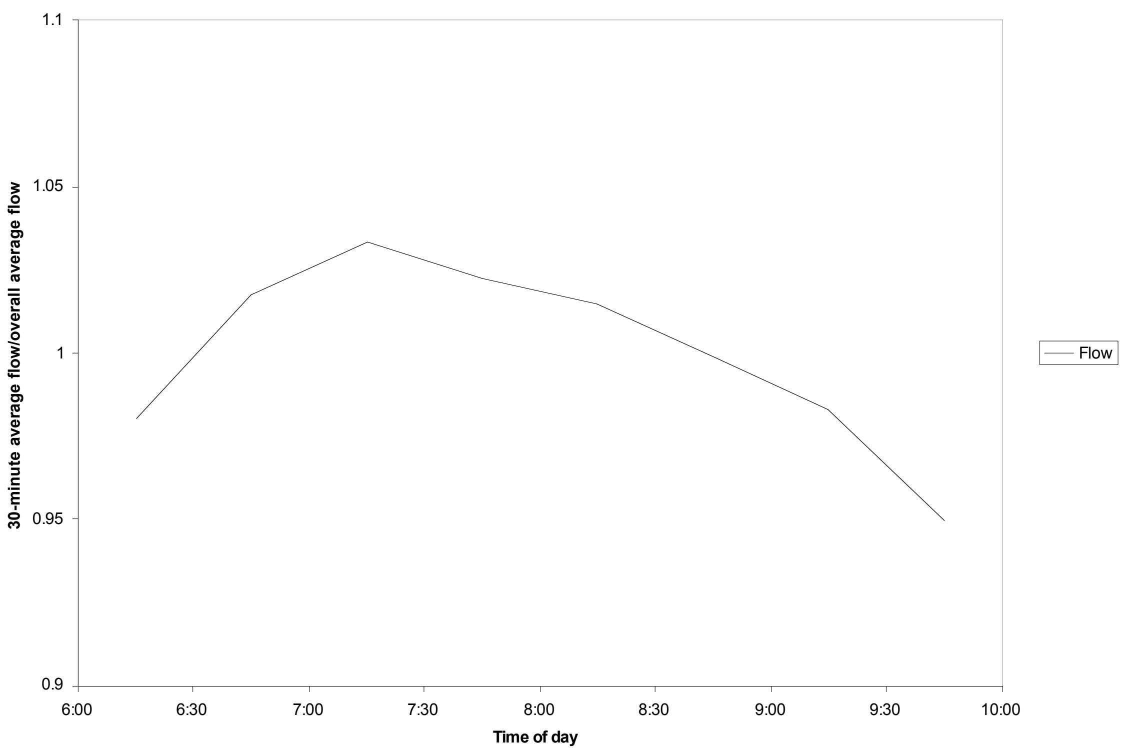


Figure C2 Variation of Queue Discharge Flow by Time of Day at Site SD-03

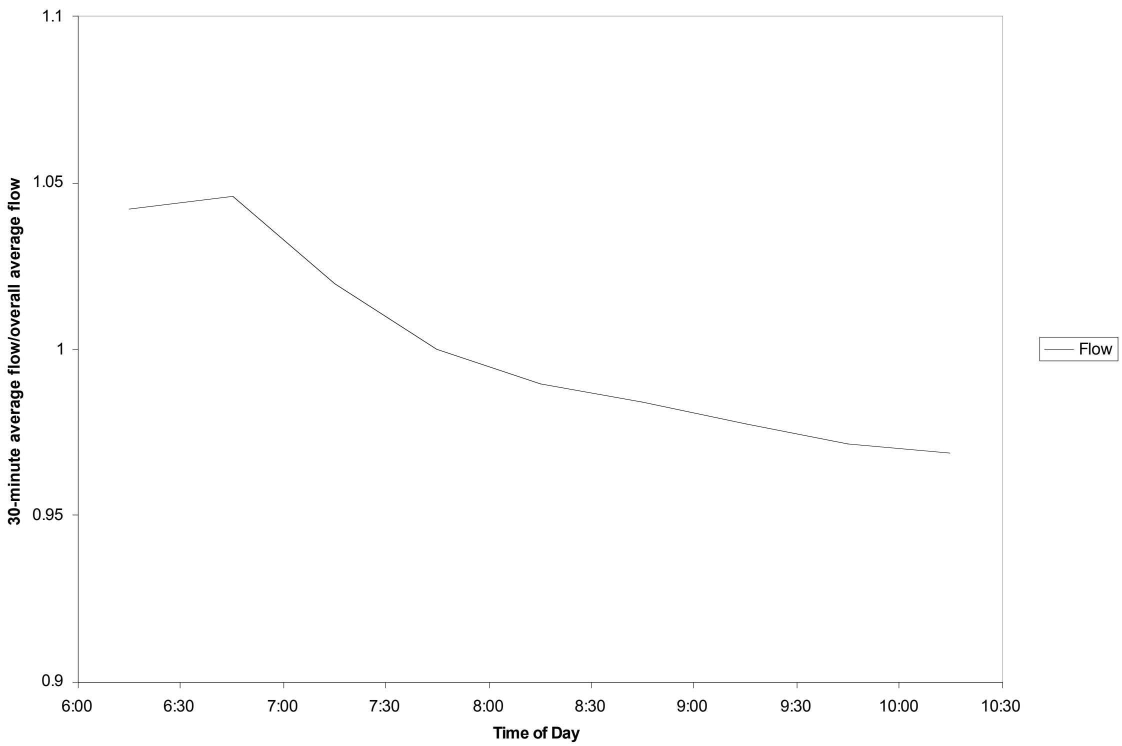


Figure C3 Variation of Queue Discharge Flow Characteristics by Time of Day at Site SD-07

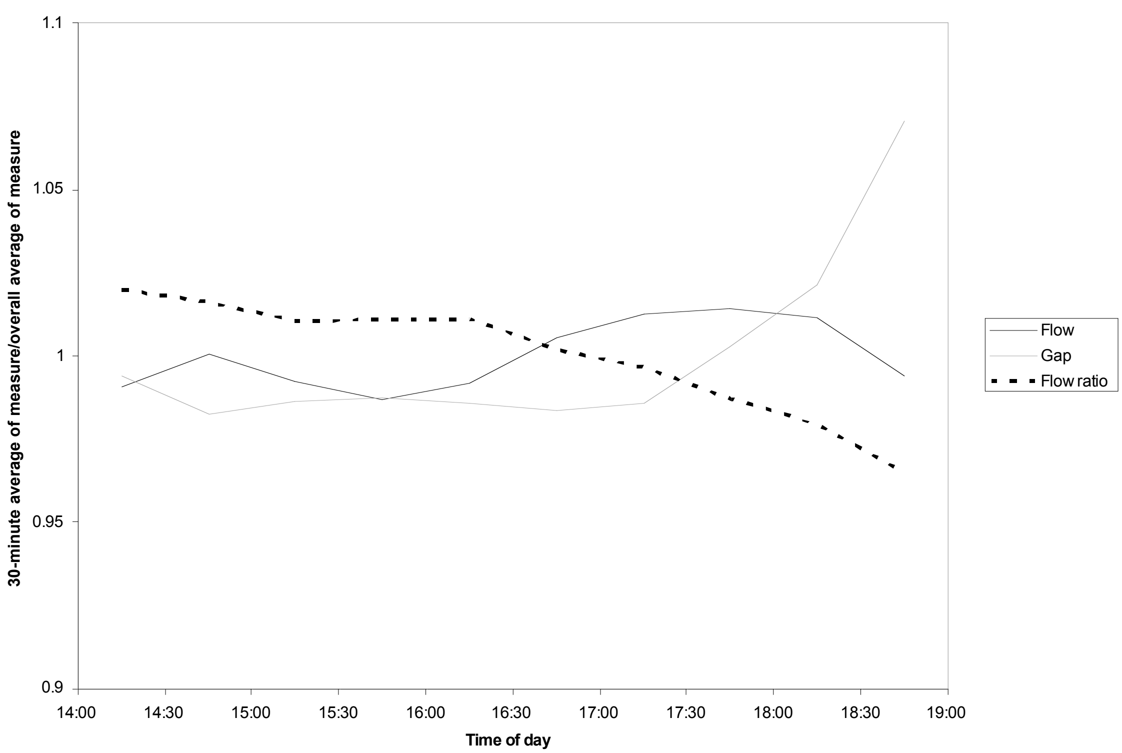


Figure C4 Variation of Queue Discharge Flow Characteristics by Time of Day at Site SD-08

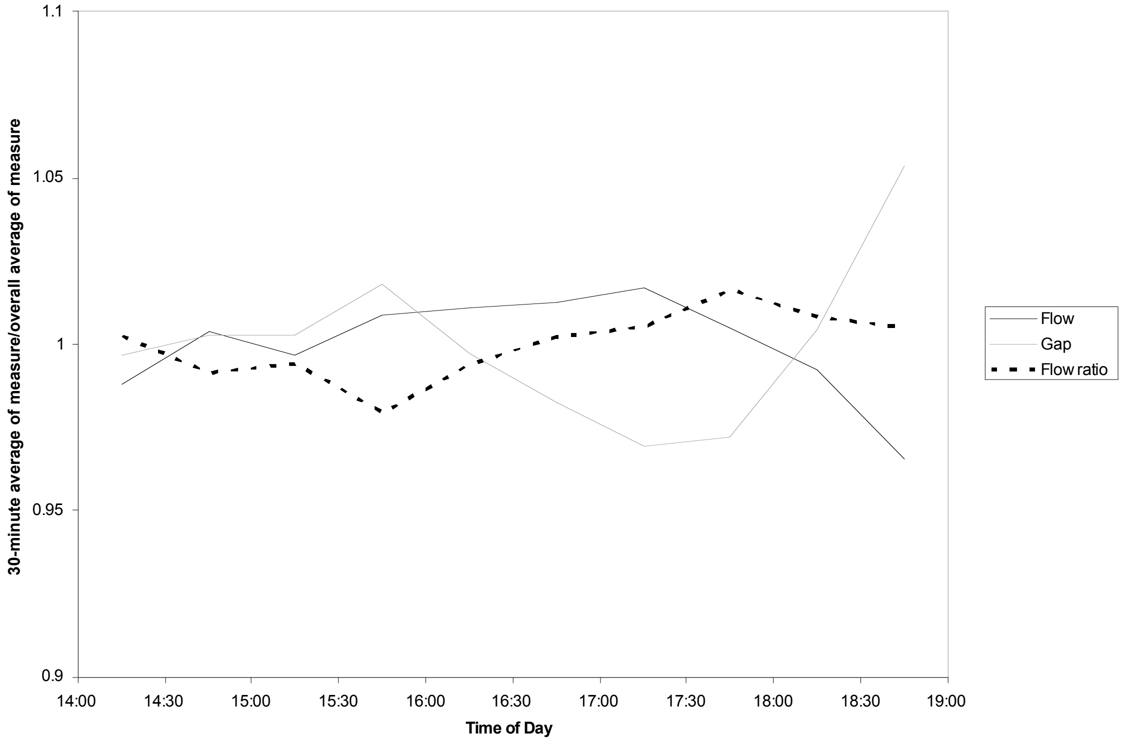
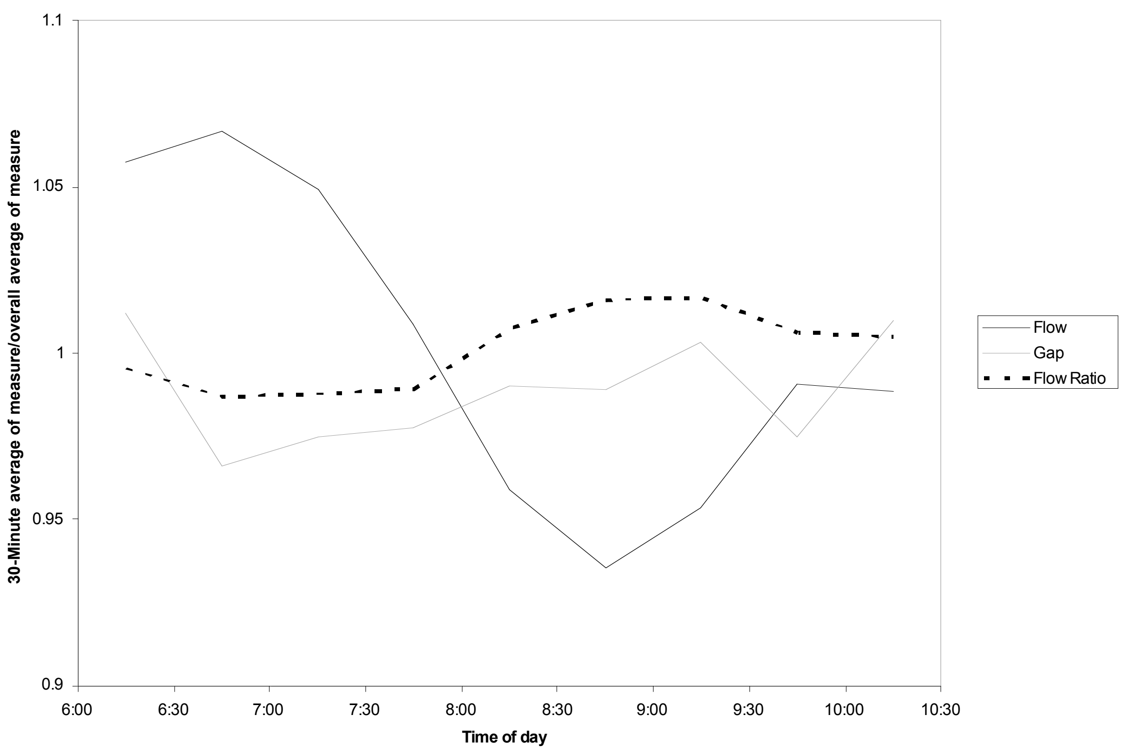


Figure C5 Variation of Queue Discharge Flow Characteristics by Time of Day at Site WA-04



Note that, at all morning peak sites (SD-01, SD-03, and WA-04), there was a tendency for QDF to peak shortly after the normal time of flow breakdown and to decline somewhat thereafter. At SD-01, the peak discharge is shown as occurring at between 7:00 and 7:30; however, there was a consistent error in the times reported by the detectors at this site and the true peak was roughly 30 minutes earlier. At both SD-02 and WA-04, QDF peaked between 6:30 and 7:00. At WA-04 it declined sharply thereafter, and then recovered somewhat after 9:00. Note that the levels and the specific patterns of variation differ among these sites, with the largest decline occurring at WA-04 (12.3 percent between the 6:30 to 7:00 time interval and the 8:30 to 9:00 interval) and the smallest occurring at SD-03 (about 7.4 percent). At the two afternoon peak sites (SD-07 and SD-08) queue discharge rates tended to increase slightly from the time of initial flow breakdown (normally between 14:00 and 14:30) and peak between 17:00 or 18:00. Variation in QDF was less for the evening peak sites than the morning peak sites, with the difference between the highest and lowest 30-minute intervals being about 5 percent or less.

The interrelationships among changes by time of day in flow, CLFR, and gap also vary from site to site. From Equation 11, flow should vary inversely with the CLFR, gap, and average passage time; consequently, changes in QDF with time of day might result from changes in gaps, changes in lane flow distributions, or changes in speed or vehicle size that would result in changes in passage times. In the cases of the afternoon peak sites (SD-07 and SD-08), CLFR and gap tended to vary inversely with one another; depending on the time period, the flow varied directly or inversely with either measure. In the case of WA-04, on the other hand, the CLFR and gap tended to vary directly with each other, and QDF varied inversely with both measures. This seems to indicate that, although QDF tends to be highest early in the morning peak and late in the afternoon peak, and thus (presumably) to correlate with the presence of commute traffic, the behavioral basis this relationship is not simple: changes occur in both gaps and lane flow distributions as the character of the flow changes.

APPENDIX D

SITE CHARACTERISTICS

Table D1 Geometric Characteristics of Study Sites

Site	Number of lanes	Grade, %	Length of grade, km
Analysis sites			
MN-02	2	-3.90	?
MN-08	3	-1.50	?
MN-14	3	-1.60	0.8
MN-18	2	+0.80	0.9
MN-21	2	+0.35	0.6
MN-22	2	-0.43	1.1
MN-23	3	+2.00	0.8
MN-25	2	+0.43	0.2
SD-05	4	+2.00	> 1.00
SD-07	4	-3.00	0.75
SD-08	4	+2.20	0.94
WA-01	3	+0.36	?
WA-02	2	+1.11	in vertical curve
WA-03	3	+1.65	0.43
WA-04	2	-0.20	1.50
Verification sites			
SD-01	4	+3.00	0.75
SD-02	4	-0.80	0.3
SD-03	4	+3.00	0.75
SD-06	4	+3.00	0.5
SD-09	4	-0.76	?
SD-12	5	+2.80	2.6

Table D2 Vehicle Classification Data

Site	% heavy vehicles, 24 h	% heavy vehicles, peak	f_{HV}
Analysis sites			
MN-02	4.27		0.979
MN-08	4.13		0.980
MN-14	3.30		0.984
MN-18	8.80		0.962
MN-21	7.98		0.964
MN-22	7.52		0.964
MN-23	5.07		0.975
MN-25	8.19		0.961
SD-05	6.50	1.10	0.969
SD-07	7.10	1.91	0.966
SD-08	6.26	1.63	0.970
WA-01	2.85	1.73	0.986
WA-02	4.83	2.70	0.976
WA-03	6.02	3.39	0.971
WA-04	3.91	4.39	0.981
Verification sites			
SD-01	7.10		0.966
SD-02	6.00		0.971
SD-03	3.80		0.981
SD-06	3.80		0.981
SD-09	3.70		0.982
SD-12	3.70		0.931

Table D3 Population Characteristics

Site	Median age, yr.	Median income, $/yr.	% male, 18-24	% Coll. grad.	Pop. Density, persons/mi^2
Analysis sites					
MN-02	34.6	48,498	4.07	33.29	2,738
MN-08	29.2	27,730	7.51	36.68	10,365
MN-14	27.9	28,847	10.21	37.35	7,232
MN-18	33.9	57,339	3.50	39.86	1,613
MN-21	36.1	40,765	5.08	25.53	2,921
MN-22	36.1	40,765	5.08	25.53	2,921
MN-23	28.4	30,522	6.92	32.64	7,475
MN-25	33.7	55,964	3.62	37.48	1,721
SD-05	30.6	33,554	5.14	17.40	7,274
SD-07	31.9	41,525	5.00	22.02	1,436
SD-08	31.6	31,322	5.27	24.45	6,702
WA-01	34.5	51,726	4.17	42.33	3,045
WA-02	32.6	47,630	4.65	30.23	2,584
WA-03	31.7	40,288	5.67	22.62	4,063
WA-04	34.6	46,298	4.21	31.83	3,421
Verification sites					
SD-01	31.9	41,525	5.00	22.02	1,436
SD-02	32.4	40,089	4.96	17.92	6,927
SD-03	37.0	53,063	3.27	46.80	1,639
SD-06	37.0	53,063	3.37	46.80	1,639
SD-09	33.4	35,412	5.06	19.15	4,766
SD-12	33.2	35,412	5.88	21.46	4,979