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Modifying Ramp Management Strategies to Enhance Resiliency of Freeway Facilities

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EXCUTIVE SUMMARY

Chapter 26 of the HCM6 suggests a procedure for the empirical estimation of freeway capacity, which is based on the direct estimation of breakdown probabilities for bins of traffic volumes. The paper expounds that this methodology is unsuitable to obtain reliable capacity estimations. The theoretical analysis of the deficiencies of the methodology is supported by empirical capacity estimations for twelve freeway sections in California. Based on the empirical results, alternatives for the HCM6 capacity estimation methodology based on statistical models for censored data as well as the distribution of pre-breakdown volumes are proposed and validated. Once the models for censored data is implemented to estimate a reliable capacity distribution function for the freeways, it is used to modify an existing ramp metering algorithm.

Keywords: Capacity, Breakdown Probability, Freeway

1- INTRODUCTION

Capacity is one of the most essential parameters for the quality-of-service assessment of freeway segments and interchanges. Capacity is generally defined as "the maximum sustainable hourly flow rate at which persons or vehicles reasonably can be expected to traverse a point or a uniform section of a lane or roadway during a given time period under prevailing roadway, environmental, traffic, and control conditions" (*1*). According to this definition, the capacity of freeway segments can be influenced by

- geometric parameters including lane width, grade, and lateral clearance,
- weather, lightness, and visibility conditions,
- the composition of vehicles and drivers in the traffic stream, mainly represented by the truck percentage and the share of drivers who are familiar with the roadway (particularly commuters),
- traffic control conditions including static and variable speed limits,
- collisions and incidents.

As some of these factors and particularly the individual drivers' behavior and their reaction on all influencing factors are stochastic in nature, it is well known that capacity must be treated as a random variable (e.g. *2–6*). Nevertheless, highway capacity guidelines still use deterministic (constant) capacities depending on well-defined systematic influencing factors in order to provide a foundation for planning decisions. In the recent evolution of the guidelines, however, traffic assessment procedures addressing both the systematic and the stochastic variability of capacity have increasingly been implemented. These developments particularly include new procedures for the evaluation of traffic reliability as well as approaches for the empirical estimation of design capacities based on field data. The latter aspect is addressed in this paper.

The HCM6 (*1*) quality-of-service assessment procedure for basic freeway segments provides base capacities depending on the free-flow speed, which represent ideal roadway, environmental, traffic, and control conditions. These base capacities can be further calibrated by capacity adjustment factors to account for systematic influencing factors including driver population, share of connected and automated vehicles, weather conditions, incidents, and work zones. For applications in which detailed traffic data from field measurements are available, chapter 26 of the HCM6 suggests a procedure for the empirical estimation of freeway capacity. This procedure is based on the direct estimation of breakdown probabilities for bins of traffic volumes. Traffic volumes measured in fluid traffic are allocated to bins of flow rates and distinguished on whether or not they were followed by a traffic breakdown. The ratio of the number of pre-breakdown intervals and the total number of observations is then regarded as the probability of breakdown at the average flow rate in each bin. However, as previous investigations (*7*, *8*) already revealed, this approach is unsuitable to obtain reliable capacity estimations. In this paper, the theoretical deficiencies of the methodology are expounded and supported by empirical capacity estimations for twelve freeway cross sections in California. Based on the empirical results, alternatives for the HCM6 capacity estimation methodology based on statistical models for censored data as well as the distribution of pre-breakdown volumes are discussed.

The paper starts with a literature review, followed by a brief review of methods to estimate capacity distribution functions. The next section summarizes the HCM6 (*1*) methodology for the estimation of freeway capacity and its theoretical deficiencies. The deficiencies of the method as well as alternative approaches are then demonstrated based on the analysis of field data from freeways in California. Finally, capacity distribution function of a freeway segment (located in California) is estimated based on the alternative approach, and its ramp metering algorithm is modified to meter the freeway onramp based on the optimum volume and occupancy of the mainline section.

2- LITERATURE REVIEW

Several studies have demonstrated that freeway capacity may vary even under the same external and prevailing conditions (*2–9*). These studies have proposed different techniques to estimate the capacity distribution function to quantify its variability more precisely.

Elefteriadou et al. (*2*) studied merge bottlenecks and realized that breakdown events may occur at flow rates lower than the conventional capacity values. They also discovered that at the same bottleneck, a given flow rate may or may not result in a traffic breakdown, implying that freeway capacity has a stochastic nature. Lorenz and Elefteriadou (4) estimated the probability of breakdown at different flow rates by allocating the hourly flow rates into bins of 100 veh/hr/ln and dividing the number of pre-breakdown intervals by the total number of intervals for each bin to calculate the probability of breakdown. The authors also observed that higher flow rates corresponded to higher probabilities of breakdown.

Brilon et al. (*5, 6*) drew an analogy between lifetime data analysis and roadway capacity analysis and employed models for censored data to estimate the capacity distribution function. They used the Product-Limit Method (PLM) to estimate the non-parametric capacity distribution function and applied the Maximum-Likelihood (ML) technique to estimate parameters of the distribution function. Results of the parametric analysis showed that capacity of German Autobahns is best represented by the Weibull distribution function.

Geistefeldt and Brilon (*7*, *8*) compared the direct breakdown probability estimation method with the capacity analysis methodology based on models for censored data and found that the capacity distribution functions estimated by the two methodologies are significantly different. By using a macroscopic simulation model, they also found that consistent capacity estimations can only be obtained by using models for censored data.

Aghdashi et al. (*9*) proposed an 8-step procedure to develop the capacity distribution function. Similar to the direct breakdown probability estimation method, this procedure also allocated the hourly flow rates into bins of 100 pc/hr/ln to calculate the probability of breakdown in each bin. Next, a Weibull distribution function was fitted to the resulting probabilities and parameters of capacity distribution function were estimated. Real-world application of this method revealed that the estimated capacity distribution function is independent of the demand profile. The authors also suggested selecting the volume corresponding to the 15% breakdown probability in case selection of a single capacity value is desired. The findings of this research were incorporated in the HCM6 (*1*).

Elefteriadou et al. (*20*) incorporated the concept of randomness of capacity in ramp metering. In their research, the authors modified two ramp metering algorithms by determining the maximum acceptable upstream volume as a function of metering rates and the acceptable probability of breakdown.

Shojaat et al. (*10, 11*) applied the models for censored data to estimate the capacity distribution function of US freeways and implemented the Sustained Flow Index (SFI), as a joint performance measure, to select a single capacity value from the distribution function. The volume that maximizes the SFI, referred to as the optimum volume, was found to be a good estimate of the freeway capacity. It was observed that the optimum volume of the capacity distribution function estimated based on 5-minute intervals corresponds well to the 15^{th} percentile of the distribution function estimated based on 15-minute intervals, which is suggested in the HCM6 for selecting a single value from the capacity distribution function.

3- METHODS TO ESTIMATE CAPACITY DISTRIBUTION FUNCTIONS

If freeway capacity is regarded as a random variable, methods to determine its distribution function based on field measurements are required. The capacity distribution function represents the probability that the capacity is equal to or less than the flow rate:

$$F_c(q) = p(c \le q) \quad (1)$$

where
$F_c(q)$ = capacity distribution function
p = probability
c = capacity (veh/h)
q = flow rate (veh/h)

The capacity distribution function $F_c(q)$ is equivalent to the probability of a traffic breakdown at the flow rate q. According to the definition of capacity, every flow rate greater than the capacity will lead to a traffic breakdown. Conversely, this means that in any interval prior to a breakdown, the demand volume must have exceeded the capacity. Hence, the traffic volume observed at a bottleneck in a pre-breakdown interval, which triggered the change of the traffic state from fluid into congested flow conditions, can be regarded as the momentary capacity of the bottleneck. It is important to note that this capacity volume is lower than the demand volume in the pre-breakdown interval, because otherwise a breakdown wouldn't have been occurred.

For the empirical estimation of capacity distribution functions based on field data, different methodologies were proposed, which can basically be allocated into two groups (*7*):

- the "direct" estimation of breakdown probabilities by calculating the ratio of the number of pre-breakdown intervals and the total number of intervals for bins of traffic volumes (*2*, *3, 9*), and
- the estimation of capacity distribution functions based on statistical models for censored data (*5–8*), in the following referred to as "Censored Data Method" (CDM).

Both approaches are based on the same definition of capacity and can be applied to data samples consisting of pairs of values of traffic volumes and speeds in short time intervals (e.g. 5 minutes). In both approaches, the observed volumes are classified into

- volumes observed during fluid traffic conditions in intervals that were followed by a breakdown (pre-breakdown), i.e. a sudden drop of the average speed to the next time interval,
- volumes observed during fluid traffic conditions in intervals that were not followed by a breakdown, and
- volumes observed during congested flow conditions (post-breakdown), which do not contain any information about the capacity in fluid traffic, which differs from the post-breakdown capacity due to the capacity drop phenomenon (*12, 13*), and therefore are disregarded.

In the following, both capacity estimation approaches are described in more detail.

3-1- Direct Estimation of Breakdown Probabilities

For the direct estimation of breakdown probabilities, the measured traffic data are binned into groups of traffic volumes. For each group i, the number of pre-breakdown intervals N_i and the total number of observations n_i are determined. The breakdown probability $F_c(q_i)$ is calculated as the ratio of the number of breakdown intervals and the total number of observations in group i:

$$F_c(q_i) = \frac{N_i}{n_i} \quad (2)$$

where
$F_c(q_i)$ = breakdown probability at flow rate q_i
N_i = number of pre-breakdown intervals in group i
n_i = total number of intervals in group i
q_i = average flow rate in group i (veh/h)

The method delivers a set of average flow rates and corresponding breakdown probabilities for each group. Depending on the data sample, the method does not necessarily deliver increasing breakdown probabilities with increasing flow rate, and the breakdown probability will only reach a value of 1 if the bin with the greatest volumes contains pre-breakdown observations only. The breakdown probabilities can be described by a mathematical distribution function by means of nonlinear regression analysis.

As previous studies (*7*, *8*) revealed, a major drawback of the direct breakdown probability estimation method arises from the fact that the difference between the traffic demand and the capacity in pre-breakdown intervals is not accounted for. In eq. (2), the number of traffic breakdowns N_i represents capacity observations, whereas the number of all intervals n_i represents both capacity and (mostly) demand observations. As the volume in the breakdown interval is limited by the capacity, it is smaller than the demand. Hence, capacity observations are allocated to lower volume classes. Thus, the direct estimation method significantly underestimates the breakdown probability at high traffic volumes and is therefore unsuitable to deliver reliable estimations of the capacity distribution function.

3-2- Capacity Estimation based on Statistical Models for Censored Data

The use of statistical models for censored data for the estimation of freeway capacity distribution functions was first proposed by van Toorenburg (*14*), also cf. (*15*), and further elaborated by Brilon et al. (*5*, *6*). In this approach, volumes observed during fluid traffic conditions in intervals that were not followed by a breakdown are considered as “censored” observations, which means that the desired value – here: the capacity – cannot be directly measured, but it can be concluded that the capacity must have been greater than the observed volume. In contrast, in intervals that were followed by a breakdown, the observed volumes represent the capacity and hence are classified as “uncensored” observations.

Samples that include censored data are well-known from lifetime data analysis. To estimate distribution functions based on data samples that include censored values, both non-parametric and parametric methods are available. For a non-parametric estimation of the capacity distribution function, the Product-Limit Method (PLM, *16*) can be applied (*5*, *6*):

$$F_c(q) = 1 - \prod_{i:q_i \le q} \frac{k_i - d_i}{k_i}, \; i \in \{B\} \quad (3)$$

where
q = flow rate (veh/h)
q_i = flow rate in interval i (veh/h)
k_i = number of intervals with a flow rate of $q \ge q_i$
d_i = number of breakdowns at a flow rate of q_i
$\{B\}$ = set of breakdown intervals

Eq. (3) delivers a set of flow rates and corresponding breakdown probabilities, which monotonically increase with increasing flow rate. The distribution function will only reach a value of 1 if the maximum observed volume is an uncensored value. Otherwise, the distribution function terminates at a value of $F_c(q) < 1$, where q is the maximum uncensored volume.

For a parametric estimation, a specific type of the distribution function is assumed whose parameters can be estimated with the Maximum-Likelihood technique. The Likelihood function to estimate the capacity distribution function is (*5*, *6*):

$$L = \prod_{i=1}^{n} f_c(q_i)^{\delta_i} \cdot \left[1 - F_c(q_i)\right]^{1-\delta_i} \tag{4}$$

where
$f_c(q_i)$ = statistical density function of the capacity c
$F_c(q_i)$ = cumulative distribution function of the capacity c
n = number of intervals
δ_I = 1, if interval i contains an uncensored value
δ_I = 0, if interval i contains a censored value

For ease of computation, the Log-Likelihood function L* can be maximized instead of the Likelihood function L:

$$L^* = \ln(L) = \sum_{i=1}^{n} \left\{ \delta_i \cdot \ln\left[f_c(q_i)\right] + (1-\delta_i) \cdot \ln\left[1 - F_c(q_i)\right] \right\} \tag{5}$$

Statistical models for censored data were successfully used to estimate capacity distribution functions in a number of recent studies (*17–19*). The consistency of the capacity estimation was proven by applying the estimation method to synthetic traffic data generated with a macroscopic simulation model in which a specific capacity distribution function was predefined (*7*, *8*).

Once the capacity distribution function is estimated, the Sustained Flow Index (SFI) can be calculated as the product of the traffic volume (q_i) and the probability of survival at this volume ($S_c(q_i)$). The SFI, which represents the "theoretical average volume that is sustained without a traffic breakdown" (*10, 11*), is given in Equation (6).

$$\mathrm{SFI} = q_i \cdot S_c(q_i) = q_i \cdot (1 - F_c(q_i)) \tag{6}$$

Where
SFI = sustained flow index (veh/h)
$S_c(q_i)$ = probability of survival at volume q_i
$F_c(q_i)$ = probability of breakdown at volume q_i
q_i = traffic volume in interval i (veh/h)

It is desirable to increase both the probability of survival and the traffic volume for a given freeway section. But, since any increase of volume necessarily leads to a decrease of the survival probability and vice versa, the SFI (as the product of the two) provides a joint performance measure. Thus, the volume that leads to the maximum SFI can be regarded as the best compromise between maximizing the throughput and minimizing the risk of a traffic breakdown. Assuming a Weibull-type capacity distribution, this optimum volume (q_{opt}) is defined in Equation (7).

$$q_{opt} = \beta(\frac{1}{\alpha})^{\frac{1}{\alpha}} \quad (7)$$

The distribution function of the critical (pre-breakdown) occupancy, i.e. the occupancy at capacity, can be estimated in the same way as the capacity distribution function if the flow rate q in Equations (3) and (4) is replaced by the occupancy o. The SFI can also be converted into a "Sustained Occupancy Index" SOI by replacing the flow rate q with the occupancy o in Equations (6).

3-3- HCM6 Capacity Estimation Methodology

In addition to the analytical quality-of-service assessment methods for freeway segments and interchanges, chapter 26 of the HCM6 (*1*) includes a procedure for estimating freeway capacity based on field data. This procedure

- is based on flow data aggregated into 15-minute intervals,
- provides detailed guidance for the selection of suitable detectors relative to the bottleneck location, including a downstream and an upstream detector used to exclude speed drops due to spillback from further downstream and to check whether queues form as a result of the breakdown,
- requires traffic data over a period of at least several months including recurring traffic breakdowns, measured under similar operational and weather conditions,
- applies the direct breakdown probability estimation method as described above,
- suggests to use the Weibull distribution for fitting a distribution function to the estimated breakdown probabilities,
- selects the 15th percentile of the breakdown probability distribution as the resulting capacity value.

As the HCM6 (*1*) procedure is based on the direct breakdown probability estimation method, the deficiencies of this approach described above also apply. The consequences of these deficiencies for the application of the capacity estimation procedure are demonstrated in the following chapter, which also discusses more suitable approaches.

4- FIELD DATA ANALYSIS

To examine the HCM6 (*1*) procedure, twelve urban freeway bottlenecks with different parameters were selected for analysis. All bottleneck sections are located in California, U.S., and their 5-minute speed and volume data were collected from the Caltrans Performance Measurement System (PeMS) website. All data samples cover at least one year to ensure reliable estimation of the capacity distribution. Table 1 shows the general characteristics of the bottleneck sections, such as the number of lanes, Average Daily Traffic (ADT), and truck percentage. Traffic data from weekends and holidays were disregarded to reduce the potential impact of unfamiliar drivers on the estimated capacity distribution functions.

Table 1. Characteristics of the bottleneck sections under study.

No.	Detector ID	Lanes	Freeway	Location	ADT (veh/d)	% Trucks
1	808945	2	SR60-WB	Riverside	59,925	< 1%
2	766694	2	SR14-NB	Los Angeles	42,929	4.98%
3	765106	3	US101-SB	Los Angeles	54,738	5.16%

4	770243	3	I210-WB	Santa Clarita	57,400	11.75%
5	1117734	4	I-5 SB	San Diego	75,659	5.59%
6	1108659	4	I-5 NB	Oceanside	104,165	5.00%
7	1209276	4	I405-SB	Santa Ana	128,912	1.20%
8	1108473	4	I5-SB	Encinitas	104,777	< 1 %
9	1108667	4	I5-SB	San Diego	84,517	1.29%
10	1111564	5	I-8 EB	San Diego	113,506	2.29%
11	717804	5	I405-NB	Los Angeles	145,818	2.05%
12	1115413	5	I-8 EB	San Diego	98,405	3.36%

The empirical analysis covered the application of the HCM6 (*1*) capacity estimation procedure as well as the PLM and the Maximum-Likelihood estimation of the capacity distribution function according to eq. (3) and (5), respectively. In addition, the average pre-breakdown flow rate was determined for each bottleneck. As the HCM6 procedure is based on 15-minute intervals, whereas the capacity estimation with models for censored data is usually applied to 5-minute intervals, traffic data in both 5- and 15-minute intervals were analyzed. As detailed truck data weren't available, volumes in veh/h/ln were analyzed instead of passenger car units. Also, a lower limit of 1,200 vehicles per hour per lane for the pre-breakdown flow rate was defined, i.e. flow rates less than this limit were ignored to exclude the impact of unreported incidents on the estimated distribution functions.

Both the HCM6 (*1*) procedure and the Maximum-Likelihood estimation method are based on the assumption that freeway capacity is Weibull distributed. To compare the variability of the Weibull distribution functions estimated by both methods, the shape parameters α of the estimated distribution functions were compared for all segments under study. A higher shape parameter results in a lower variance of the capacity distribution function, which in turn results in a more reliable selection of a certain percentile of the distribution function (e.g. 15^{th} percentile as suggested by the HCM6). Moreover, the coefficients of variation (c_v) of the distribution functions, which indicate the size of a standard deviation relative to the mean, were estimated. A lower coefficient of variation suggests a lower level of dispersion around the mean.

The HCM6 (*1*) capacity estimation procedure was applied by allocating the measured flow rates into both 100- and 200-veh/h/ln bins. The estimated Weibull shape and scale parameters α and β, respectively, the coefficients of variation, as well as the 15th percentiles of the fitted Weibull-type capacity distribution functions are given in Table 2. The results show a considerable variation of the parameters estimated for different bottlenecks. The estimated Weibull shape parameters are remarkably small in most cases, which is often due to the low share of breakdown intervals in the bins with the highest flow rates. Even for the same segment, the bin size (100- or 200-veh/h/ln) significantly affects the distribution parameters in some cases.

Table 2. Shape and scale parameters α and β, coefficients of variation c_v, and 5^{th} and 15^{th} percentiles $q_{5\%}$ and $q_{15\%}$ of the Weibull distribution function estimated with the HCM6 (*1*) capacity estimation procedure based on 5- and 15-minute data (sample no. as in Table 1).

No.	Bin	5-minute intervals				15-minute intervals			
		Weibull α (-)	Weibull β (veh/h/ln)	c_v (-)	$q_{5\%}$ (veh/h/ln)	Weibull α (-)	Weibull β (veh/h/ln)	c_v (-)	$q_{15\%}$ (veh/h/ln)
1	100	4.3	3167	0.26	1586	4.6	2631	0.25	1774
	200	2.6	5043	0.41	1592	2.1	5351	0.50	2221

2	100	3.9	3789	0.29	1781	9.1	2300	0.13	1882
	200	7.5	2774	0.16	1864	7.7	2403	0.15	1898
3	100	2.7	5578	0.40	1852	7	2441	0.17	1886
	200	3.1	4878	0.35	1898	7.6	2402	0.16	1891
4	100	3.3	4120	0.33	1665	8.4	2116	0.14	1704
	200	6.3	2716	0.19	1692	8.7	2108	0.14	1712
5	100	7.6	2479	0.16	1680	12.3	2004	0.10	1729
	200	11.7	2278	0.10	1769	10.1	2068	0.12	1727
6	100	4.6	3090	0.25	1621	12.5	2057	0.10	1780
	200	2.6	5173	0.41	1647	10.6	2109	0.11	1777
7	100	2.9	5157	0.37	1836	10.9	2400	0.11	2032
	200	2.9	5153	0.37	1866	9	2484	0.13	2028
8	100	16.7	2275	0.07	1903	15.8	2088	0.08	1861
	200	14.7	2325	0.08	1901	13.7	2142	0.09	1875
9	100	4.9	3494	0.23	1914	8.7	2341	0.14	1901
	200	3.4	4754	0.32	1990	9	2323	0.13	1898
10	100	19.9	2379	0.06	2049	12.3	2288	0.10	1974
	200	10.1	2617	0.12	1950	11.1	2318	0.11	1967
11	100	13.6	2247	0.09	1805	15.1	2029	0.08	1799
	200	11.2	2276	0.11	1747	10.6	2116	0.11	1783
12	100	2.9	4242	0.37	1523	3.9	2887	0.29	1822
	200	2.1	5851	0.50	1447	1.6	8501	0.64	2751

The results of the capacity estimation with the Maximum-Likelihood method and the determined average pre-breakdown flow rates are given in Table 3. The variances of the estimated distributions are significantly lower than those estimated with the HCM6 (*1*) capacity estimation procedure and differ much less between the analyzed bottlenecks. In Figure 1 and Figure 2, the estimated capacity distribution functions are compared for two example freeway sections.

Table 3. Average pre-breakdown flow rates $\bar{q}_{pre\text{-}bd}$, shape and scale parameters α and β, coefficients of variation c_v, and 5th and 15th percentiles $q_{5\%}$ and $q_{15\%}$ of the Weibull distribution function estimated with the Maximum-Likelihood method in 5- and 15-minute intervals.

No.	5-minute intervals					15-minute intervals				
	$\bar{q}_{pre\text{-}bd}$ (veh/h/ln)	Weibull α (-)	Weibull β (veh/h/ln)	c_v (-)	$q_{5\%}$ (veh/h/ln)	$\bar{q}_{pre\text{-}bd}$ (veh/h/ln)	Weibull α (-)	Weibull β (veh/h/ln)	c_v (-)	$q_{15\%}$ (veh/h/ln)
1	1768	20.2	2095	0.06	1809	1715	22.5	1920	0.06	1771
2	1917	22.5	2191	0.06	1919	1866	26.3	2028	0.05	1893
3	1801	17.2	2195	0.07	1848	1741	19.4	1997	0.06	1819
4	1756	19.2	2055	0.06	1761	1739	24.3	1889	0.05	1753
5	1880	26.7	2065	0.05	1847	1819	26.8	1935	0.05	1808
6	1831	21.4	2116	0.06	1841	1785	23.3	1961	0.05	1814
7	2130	20.1	2506	0.06	2162	2075	22.2	2312	0.06	2130
8	1902	21.1	2204	0.06	1914	1851	20.6	2069	0.06	1895
9	1984	23.9	2238	0.05	1977	1955	27.2	2098	0.05	1963
10	2028	23.1	2292	0.05	2016	1975	23.0	2162	0.05	1998
11	1873	22.6	2101	0.06	1842	1813	23.1	1981	0.05	1831

12	1680	28.6	1856	0.04	1673	1646	34.5	1747	0.04	1657

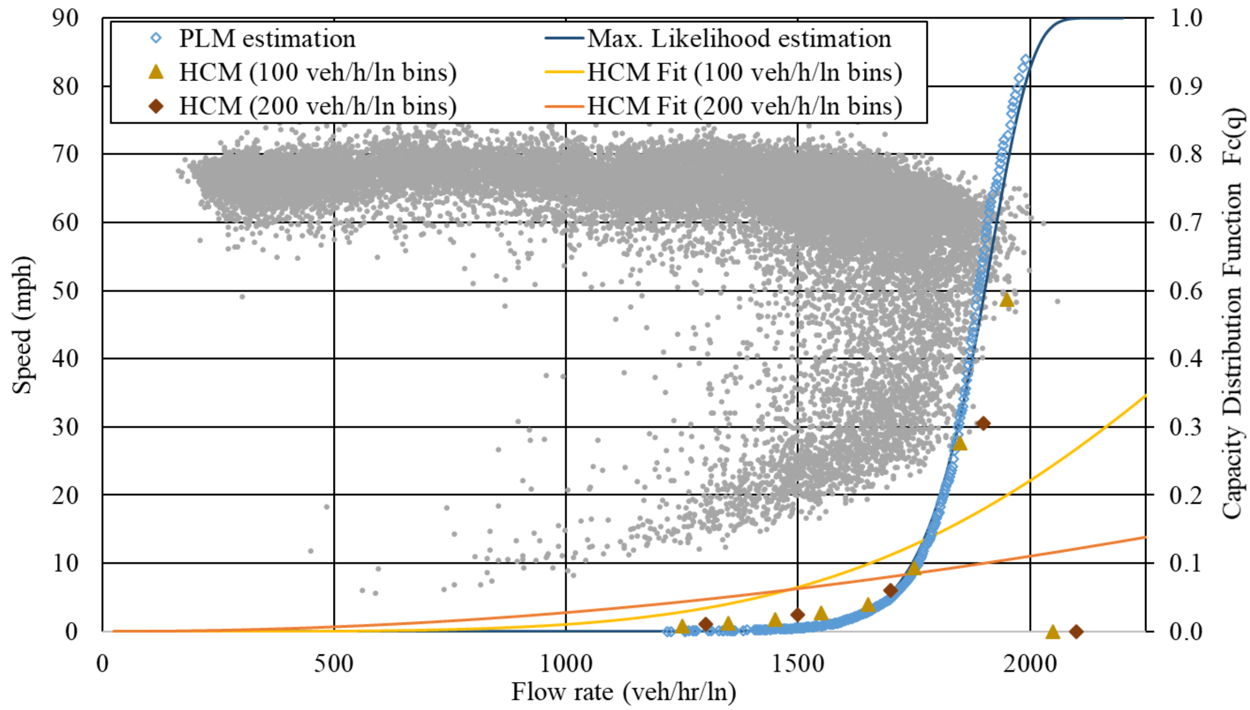

Figure 1. Capacity distribution functions estimated based on the HCM6 procedure as well as the PLM and the Maximum-Likelihood method for the 2-lane freeway cross section no. 808945 near Riverside, CA.

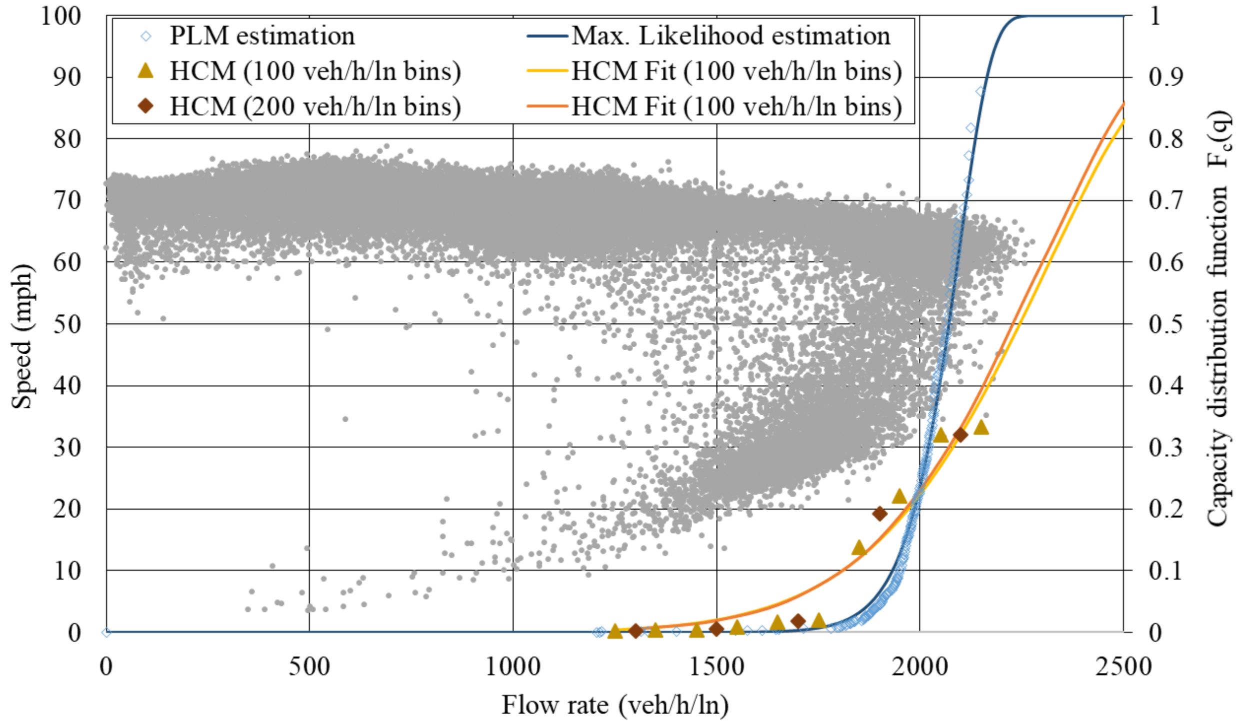

Figure 2. Capacity distribution functions estimated based on the HCM6 procedure as well as the PLM and the Maximum-Likelihood method for the 4-lane freeway cross section no. 1108667 near San Diego, CA.

The results of the comparative analysis reveal that the theoretical deficiencies of the HCM6 (*1*) capacity estimation procedure lead to implausible and unreliable capacity estimation results. The low and sometimes even decreasing breakdown probabilities obtained at the highest flow rates, which can particularly be seen in the example shown in Fig. 1, result in an unrealistically large variation of the estimated distribution functions. Although the 15^{th} percentile volume of the estimated capacity distribution varies less, the very low shape parameters α of the Weibull distribution suggest that the use of the direct probability estimation method in the HCM6 procedure is unsuitable to estimate freeway capacity.

In contrast, the capacity estimation methods based on models for censored data allow for a robust derivation of capacity distribution functions as far as sufficient traffic breakdowns are observed. The results given in Table 3 also indicate that the use of the average pre-breakdown flow rate $\bar{q}_{pre\text{-}bd}$ measured in 5-minute intervals as capacity estimate might be a simple alternative to estimating a complete capacity distribution for applications in practice. The average difference between the pre-breakdown volumes and the 15^{th} percentile volumes of the Weibull capacity distribution estimated with the Maximum-Likelihood method amounts to 18 veh/h/ln, hence the pre-breakdown flow rate is on average about 1% higher than the 15^{th} percentile volume of the capacity distribution. This correlation can be explained by the influences of the interval duration and the different analysis methods: The difference between capacities measured in 5-minute and 15-minute intervals is roughly compensated by the fact that the average pre-breakdown volume is smaller than the mean value of the capacity distribution function. If this correlation can be confirmed based on a larger number of data samples, the average pre-breakdown flow rate might be used as a simple estimate of the volume associated with a 15% breakdown probability.

5- APPLYING THE SFI TO MODIFY A RAMP METERING ALGORITHM

It has been shown that vehicle platoons entering a freeway create turbulence which has the potential to cause traffic breakdowns. Ramp management strategies have been shown to reduce this turbulence by metering the traffic at onramps through signalization. The number of vehicles prescribed to enter the freeway is usually calculated by an online adaptive traffic control that attempts to optimize the freeway performance by striking a balance between allowable turbulence of the mainline freeway and the vehicles waiting at the onramp.

In order to modify a ramp metering algorithm to meter the onramps based on the optimum volume, real-world data were collected from a freeway section located at San Diego, California. The reason behind selection of the section was that the current (in use) ramp metering algorithm at the section was kindly provided by the authorities.

The section under investigation, has two onramp lanes, consisting of a regular lane and an HOV lane that is rarely used. Due to the low volume of the HOV lane, influence of the vehicles entering from the HOV lane on probability of breakdown of the downstream mainline section could not be directly measured. Thus, in this study, the HOV volume was added to the ordinary onramp volume, and the total ramp volume was considered for analysis.

The current in use SDRMS algorithm for the section under investigation is shown in Table 4. As can be seen in the table, corresponding to each mainline volume and occupancy is a specific maximum permitted onramp volume. As soon as the mainline volume or occupancy, whichever that is more restrictive, reaches its threshold, the SDRMS allows its corresponding ramp volume to enter the freeway. If the upstream mainline volume/occupancy becomes greater than the maximum number allowed (i.e., 36.1 veh/ln/59.1seconds or 20.5 percent), the minimum ramp volume will still be allowed to enter the facility. This suggests that irrespective of the value of upstream mainline volume/occupancy, the number of ramp vehicles allowed to enter the freeway is never less than 5.45 veh/min.

Table 4. Currently used SDRMS algorithm for the section under study.

Rate Code	Upstream Occupancy (percent)	Upstream Volume (veh/ln/59.1seconds)	Total Onramp Volume (veh/min)
1	16.20	28.73	10.35
2	16.48	29.25	10
3	16.76	29.78	9.65
4	17.04	30.31	9.3
5	17.33	30.83	8.95
6	17.61	31.36	8.6
7	17.89	31.88	8.25
8	18.17	32.41	7.9
9	18.45	32.93	7.55
10	18.74	33.46	7.2
11	19.02	33.98	6.85
12	19.30	34.51	6.5
13	19.58	35.03	6.15
14	19.86	35.56	5.8
15	20.15	36.08	5.45

The SDRMS algorithm considers the minimum and maximum occupancies and volumes for the upstream mainlines. By subtracting the minimum values from the maximum and dividing the result to the difference between their rate code values, the average value of increase in volume and occupancy per increase in rate code is calculated. These are called "delta volume" and "delta occupancy", respectively. For example, as can be seen in Table 4, the upstream mainline volumes for rate code number one and number fifteen are 28.73 and 36.08 veh/ln/59.1seconds, respectively. Thus, be dividing the difference between the volumes to the difference between the rate codes (i.e., 7.37 divided by 14), delta volume of 0.5253 veh/ln/59.1seconds is obtained. By following the same steps for occupancy, delta occupancy of 0.28 is obtained. It can also be seen that the delta volume for the total ramp volume is 0.35 veh/ln/min. This means that the upstream mainline volumes and occupancies, and their respective ramp volumes increase linearly (i.e., using constant increments of delta volume and delta occupancy) in this algorithm.

To develop different capacity distribution functions for different ramp volumes, as the first step, five years of speed, volume, and occupancy data were collected for the upstream section. For the onramps, only volume data were collected. Next, different breakdown probability models were estimated for different ramp volume categories. To do this, in addition to the mainline volumes and occupancies, ramp volumes that had been grouped into different categories (e.g., < 331veh/h, 331-435veh/h, 435-518 veh/h, 518-538veh/h) were also considered for analysis and a unique probability distribution function was estimated for each category. To verify the statistical difference of the capacity distribution functions estimated for different ramp volume categories from one another, a log-rank test was performed. The log-rank test is a statistical test used for comparing the distribution functions of different categories (i.e., different ramp volume categories in this study). Under the null hypothesis, the log-rank test assumes that different distribution functions are not statistically different from one another. Thus, one should use the log-rank test to evaluate whether the selected ramp volume categories provide distribution functions that are statistically different from one another, and if not, consider other categories.

After the capacity distribution functions for different ramp volume categories were estimated, the mean values of the ramp volume categories were calculated and interpolation/extrapolation was used to estimate the capacity distribution function corresponding to any desired ramp volume (in between or outside of the categories). By trial and error, four different ramp volume categories (i.e., < 331veh/h, 331-435veh/h, 435-518 veh/h, 518-538veh/h) whose corresponding capacity distribution functions were statistically different from one another were selected for analysis.

Once the capacity distribution functions for individual ramp volumes were estimated, their corresponding SFI's, optimum volumes, and optimum occupancies were estimated as well. Figure 4.9 and Figure 4.10 show the capacity distribution functions and the SFI's developed for individual ramp volumes based on the upstream mainline volume and mainline occupancy.

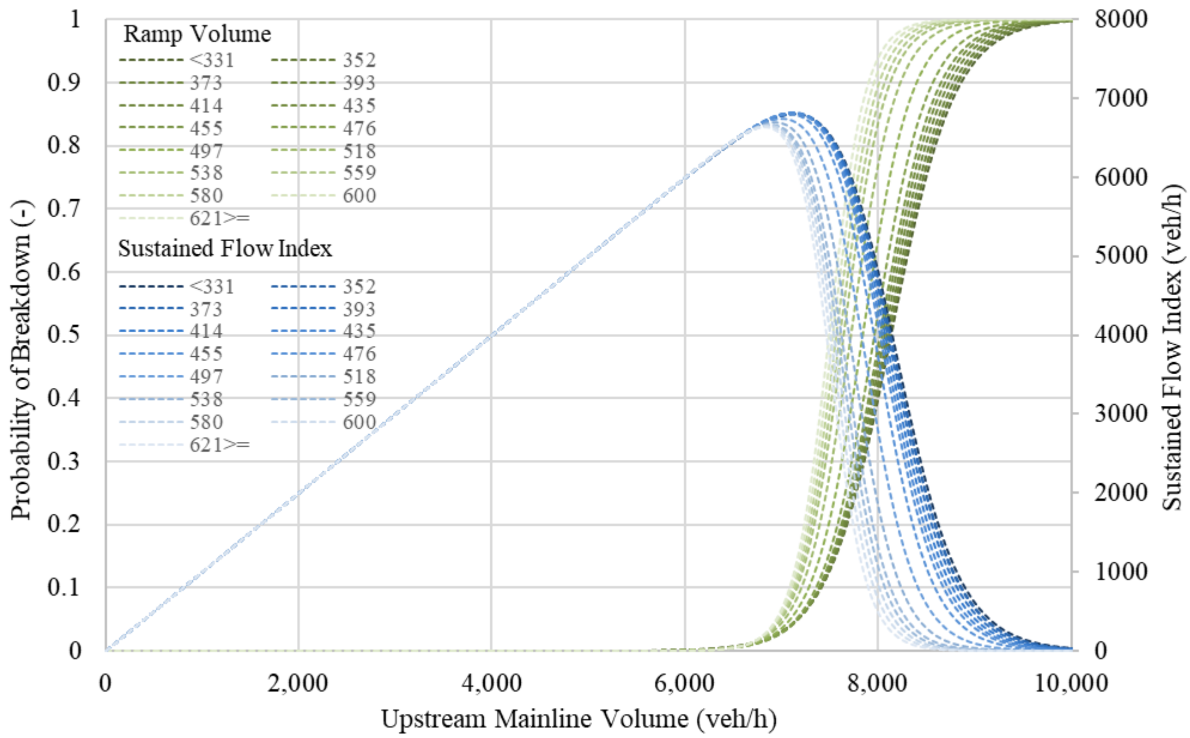

Figure 3. Capacity distribution functions and the SFI's developed for individual ramp volumes based on the upstream mainline volume.

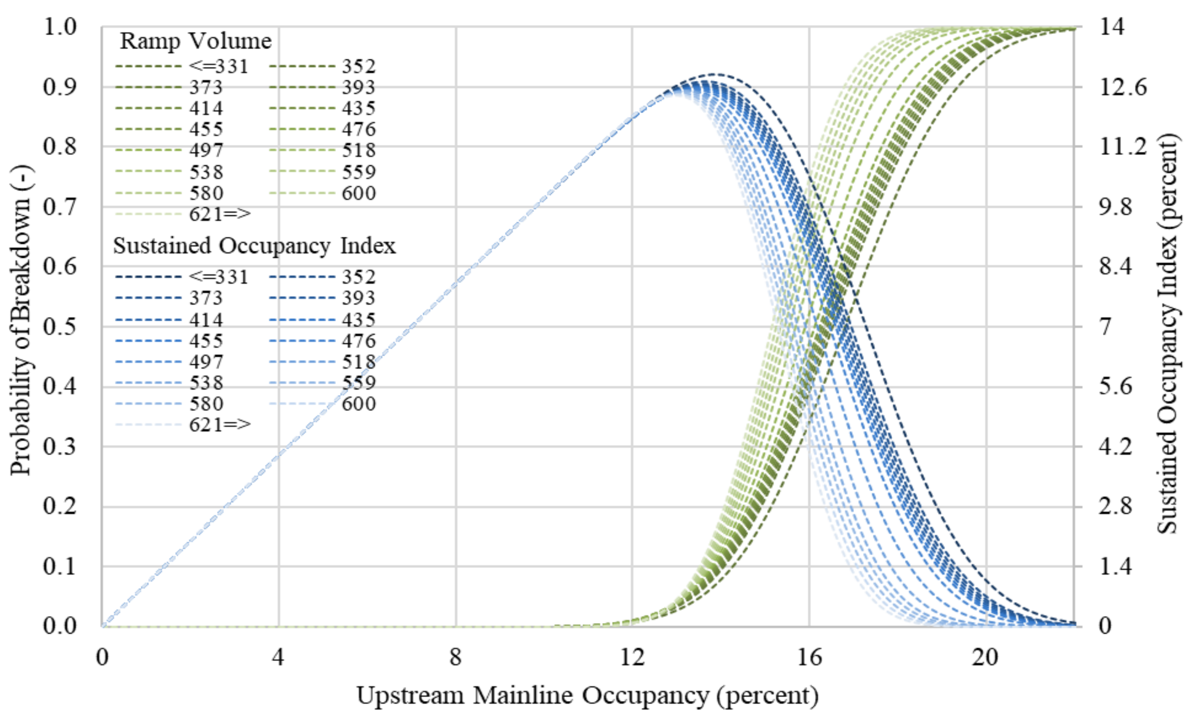

Figure 4. Capacity distribution functions and the SOI's developed for individual ramp volumes based on the upstream occupancy volume.

Table 5 shows the modified SDRMS algorithm. As required by the SDRMS, the upstream volumes were stated in terms of vehicles per lane per 59.1 seconds and the total onramp volumes were stated in terms of vehicles per minute[1].

Table 5. Modified SDRMS algorithm for the section under study.

Rate Code	Upstream Occupancy (percent)	Upstream Volume (veh/ln/59.1seconds)	Total Onramp Volume (veh/min)
1	12.99	28.016	10.35
2	13.05	28.107	10
3	13.11	28.197	9.65
4	13.18	28.288	9.3
5	13.24	28.378	8.95
6	13.30	28.468	8.6
7	13.37	28.559	8.25
8	13.43	28.649	7.9
9	13.49	28.740	7.55
10	13.55	28.830	7.2
11	13.62	28.921	6.85
12	13.68	29.011	6.5
13	13.74	29.102	6.15
14	13.81	29.192	5.8
15	13.87	29.282	5.45

The modified SDRMS algorithm shown in the table above provides a better freeway mainline performance compared to the current SDRMS algorithm. However, this algorithm cannot guarantee that metering the onramps as a function of the optimum volume of the downstream section will always deliver the best possible solution for the entire network. In fact, if solely performance of the freeway mainline (without the onramps) is of concern, then metering up to the optimum volume may optimize freeway performance. Since the optimum volume provides the best compromise between probability of breakdown and the unused capacity of the section, it is a good indicator for the maximum reliable volume that can be traversed by freeway. On the other hand, if the performance of the entire freeway facility (i.e., freeway and the onramps) is of interest, then metering to the optimum volume may lead to a suboptimal solution (especially at higher onramp volumes) due to the increased onramp queue. The optimum volume, however, reveals an important piece of information in this case: the minimum acceptable probability of breakdown is the one corresponding to the optimum volume. This suggests if an overall downstream volume (i.e., sum of mainline and onramp volumes) less than the optimum volume is selected for metering, then the capacity of road is not used sufficiently and an extra delay is imposed to the onramp vehicles.

6- CONCLUSIONS

The procedure for estimating freeway capacity based on field data given in chapter 26 of the HCM6 (*1*) is based on the direct estimation of breakdown probabilities for bins of traffic volumes. It was

[1] Instead of vehicles per hour

shown that this approach is unsuitable to obtain reliable capacity estimates, because demand and capacity observations are not treated separately. An empirical capacity analysis carried out for twelve freeway bottlenecks in California confirmed that the theoretical deficiencies of the approach result in implausible capacity estimates in many cases. In particular, the variance of the estimated capacity distribution functions is unrealistically large, which is due to rather low and sometimes even decreasing breakdown probabilities obtained at the highest flow rates.

In contrast, the capacity estimation methods based on statistical models for censored data (*5–8*) provide a well-established framework for the estimation of consistent capacity distribution functions. Applying this concept in the HCM6 procedure would only require a minor revision, because the definition of a traffic breakdown, the selection of suitable detectors, and the traffic data requirements could remain unchanged. As a simple alternative to estimating a complete capacity distribution, the use of the average pre-breakdown flow rate measured in 5-minute intervals, which turned out to be a good estimate of the 15th percentile of the capacity distribution, might also be considered. However, further research based on a higher number of data samples would be required to confirm the validity if this approach.

Finally, the SFI was applied to modify the San Diego Ramp Metering System (SDRMS) that is currently used in a section of freeway located in San Diego, California. To do this, different capacity distribution functions were developed for different ramp volumes, and their corresponding optimum volumes and occupancies were estimated and used to modify the SDRMS algorithm.

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