Capacity and Delay Estimation at Signalized Intersections under Unsaturated Flow Condition Based on Cycle Overflow Probability

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(with correction in eq.(9))

Abstract
This paper presents a model for estimating capacity and delay at signalized intersections. Making use of the queuing system at signalized intersections, the capacity can be estimated by measuring the cycle overflow probability at stop-line detectors. Based on a given queuing model, the stochastic characteristics of signalized intersections can be estimated as well. Then, delays and queuing lengths can be obtained using the estimated parameters. The results of the presented model are underlined by a comprehensive sensitivity analysis. Furthermore, a VISSIM simulation study is conducted to demonstrate the capability of the model.

Keywords: Signalized intersection; Capacity; Delay; Cycle overflow probability

1 Introduction

Capacity at signalized intersections is a basic parameter in urban transport networks. The capacity of a signalized intersection depends on existing geometric, control, weather, and other conditions. Estimation of capacity at signalized intersections is one of the most important topics in traffic engineering and transportation science. If the capacity can directly be measured, the delay or queue length at signalized intersections and thus the traffic performance and quality of service can be calculated according to the functional relationship between delay or queue length and capacity. Unfortunately, under real world traffic conditions, the capacity cannot easily be measured directly for an existing intersection, especially under unsaturated flow conditions where the demand is lower than the capacity.

This paper presents a model for estimating capacity of an existing signalized intersection under unsaturated flow condition based on the cycle overflow probability which can be directly measured by loop detectors at stop lines. The cycle overflow probability is just the proportion of the number of cycles with fully occupied detector during green phases to the total number of cycles. Also the demand can directly be measured by loop detectors at stop lines. According to the queuing theory, the cycle overflow probability is a function of the degree of saturation, i.e. a function of demand and capacity. Thus, by measuring the cycle overflow probability and the demand, the capacity can be estimated according to the functional relationship. Based on the given queuing model, the stochastic characteristics of signalized intersections can be estimated as well. Then, delays and queuing lengths can be obtained using the estimated parameters.

The proposed model can be verified by simulation studies under unsaturated conditions. For validation the model, capacities obtained for saturated flow condition (cycles with fully occupied detector during green phases) where the capacity can be considered as the measured flow rate are used as a reference.

The proposed model provides a useful tool for estimating capacity and delay at signalized intersections under unsaturated conditions. Using the proposed model, the capacity and thus the traffic quality of service at existing signalized intersections can directly be estimated using data from loop detectors at stop lines. The model is theoretically reasonable and easily to use for practitioners. The results of the calibration and validation are very promising.

The paper is organized as follows. In the following section 2, a theoretical background and motivation of the proposed model is presented. In section 3, some numerical studies are conducted in order to examine the sensibility of the model and its parameters. In section 4, possible applications of the proposed model are presented and discussed. Then, examples of the model using simulated data are illustrated in section 5. And finally, a conclusion and outlook is given in section 6.

2 Theoretical Background

The model derivation in this paper is based on the following basic conditions in traffic modelling: a) under-saturated flow condition, i.e. the degree of saturation x should be less than 1; b) stationary flow state, i.e. the mean value of traffic demand and capacity is constant over time; c) fixed-time signals, i.e. the signal control is independent of demand; and d) M/Bunch/1 queuing system, this indicates that the probability of idling state is not equal to 1 - x, where x is the degree of saturation. Notice the delay model in HCM (TRB, 2010) and HBS (FGSV, 2015) are based on an M/D/1 queuing model that overestimates delays or queue lengths under unsaturated conditions.

However, the here derived approach can be extended to following conditions without losing generality: a) non-Markovian input process; b) temporal oversaturation; b) piecewise stationarity; and d) actuated and coordinated signals.

2.1 Queuing Model at Signalized Intersections

In order to estimate the capacity and traffic state at traffic systems, Measures of Effectiveness (MOE) for the corresponding queuing systems have to be collected. For the traffic performance analysis at signalized intersections, delay and queue length are the most common MOEs. For calculating the queue length or delay at signalized intersections, the capacity and the characteristics of the queuing system must be known. Thus, the capacity C and the characteristics at signalized intersections have to be estimated in advance. However, it is not an easy issue to measure the capacity and the queuing characteristics in the reality.

The queue length and delay at signalized intersections can be estimated according to the stochastic input (demand q) and output (capacity C) process. At signalized intersections, the queue length at end of green time N_{GE} is the most crucial parameter. The value of N_{GE} can be directly measured at end of green time. Once this parameter N_{GE} is known, the corresponding delay and queue length at other stage of cycle time (e.g. end of red time or end of back-of-queue) can be calculated according existing mathematical models (cf. Wu, 1996). Another parameter which describes the characteristics of queuing system under consideration is the so-called cycle overflow probability P_o. The cycle overflow probability P_o can be obtained by measuring the detector occupancy during the green time g.

Both parameters N_{GE} and P_o are functions of demand q and capacity C. Using these functions, the capacity can be estimated by measuring the queue length N_{GE} or the probability of cycle overflow probability P_o at end of or during the green time g. Furthermore by measuring the parameters N_{GE} or P_o the characteristics of the corresponding queuing system can be estimated as well. Between the parameters N_{GE} and P_o, there is a clearly defined inter-relationship.

According to the queuing system at signalized intersections, the value of N_{GE} or P_o can be expressed as functions of the degree of saturation x and the cycle capacity m. That is, $P_o = f(x, m)$ and $N_{GE} = f(x, m)$. According to Miller (1978) is

$$P_o = \exp\left(-A\sqrt{m}\,\frac{1-x}{x}\right) = \exp\left(-A\sqrt{m}\left(\frac{1}{x}-1\right)\right) \qquad [-] \qquad (1)$$

$$N_{GE} = \frac{\exp\left(-B\sqrt{m}\,\frac{1-x}{x}\right)}{2(1-x)} = \frac{\exp\left(-B\sqrt{m}\left(\frac{1}{x}-1\right)\right)}{2(1-x)} \qquad [veh] \qquad (2)$$

with	m	=	sg	
		=	capacity per cycle	[veh]
	s	=	saturation flow rate	[veh/s]
	g	=	effective green time	[s]
	x	=	degree of saturation = $q/C = n/m$	[-]
	q	=	traffic demand	[veh/s]
	C	=	capacity demand	[veh/s]
	n	=	qc = traffic demand per cycle	[veh]
	c	=	cycle time	[s]
	A, B	=	model parameters describing the queuing characteristics, for fixed-time signals: A = 1.58 and B = 1.33 = 0.84A	

Eqs.(1) and (2) yield

$$x = \frac{-A\sqrt{m}}{\ln(P_o)} \qquad [-] \qquad (3)$$

and

$$N_{GE} = \frac{P_o^{\,0.84}}{2\left(1-\frac{-A\sqrt{m}}{\ln(P_o)}\right)} \qquad [veh] \qquad (4)$$

Wu (1990, 1996) provided two other regression functions for the two parameters as follows.

$$P_o = x^{a\sqrt{m}} \qquad [-] \qquad (5)$$

$$N_{GE} = \frac{x^{b\sqrt{m}}}{2(1-x)} = \frac{x^{0,8a\sqrt{m}}}{2(1-x)} \qquad [veh] \qquad (6)$$

with	a, b	=	model parameters describing the queuing characteristics, for fixed-time signals a = 1.77 and b = 1.42 =0.8a

These equations yield

$$x = P_o^{(\frac{1}{a\sqrt{m}})} \qquad [-] \qquad (7)$$

and

$$N_{GE} = \frac{P_o^{0.8}}{2(1-P_o^{(\frac{1}{a\sqrt{m}})})} \qquad [veh] \qquad (8)$$

Then, delays at signalized intersections can be calculated as follows (Miller, 1978; Akcelik, 1980 Webster, 1958; Webster and Cobbe, 1966; Kimber and Hollis, 1979) for a stationary queuing system as signalized intersections.

$$d = d_1 + d_2 = \frac{(1-\frac{g}{c})^2 c}{2(1-\frac{g}{c}x)} PF + \frac{N_{GE}}{q} = \frac{(1-\frac{g}{c})^2 c}{2(1-\frac{g}{c}x(P_o))} PF + \frac{N_{GE}(P_o)}{q} \qquad [s] \qquad (9)$$

where PF is the so-called progression factor accounting for signal coordination (cf. TRB, 2010).

For fixed-time signals, both approaches deliver almost identical values of and P_o (cf. Wu, 1990). Eqs. (5) and (6) have simpler structures and they are preferred in the application. The value of P_o can more easily be obtained by detectors at stop-line than the value of N_{GE}. In this paper, only the value of P_o is used for further derivations. Then, x and N_{GE} can be obtained as a function of P_o.

The parameters A and B or a and b describe the stochastic characteristics of the corresponding queuing system. The values of them can be calibrated with measured field data.

For practical reasons, the degree of saturation can be rewritten as $x = n/m$. Thus, eq. (1) yields

$$P_o = \exp\left[-A\sqrt{m}\cdot\left(\frac{1}{x}-1\right)\right] = \exp\left[-A\sqrt{m}\cdot\left(\frac{C}{q}-1\right)\right] = \exp\left[-A\sqrt{m}\cdot\left(\frac{m}{n}-1\right)\right] \qquad [-] \qquad (10)$$

And eq. (5) yields

$$P_o = x^{a\sqrt{m}} = \left(\frac{q}{C}\right)^{a\sqrt{m}} = \left(\frac{n}{m}\right)^{a\sqrt{m}} \qquad [-] \qquad (11)$$

These are very general expressions of P_o. They are no more functions of the cycle time c and the green time g.

x	m=5	m=7.5	m=10	m=12.5	m=15	m=17.5	m=20	m=22.5	m=25
0.3	0.005	0.001	0	0	0	0	0	0	0
0.4	0.018	0.007	0.003	0.001	0.001	0	0	0	0
0.5	0.05	0.026	0.014	0.008	0.005	0.003	0.002	0.001	0.001
0.6	0.111	0.072	0.049	0.034	0.024	0.017	0.012	0.009	0.006
0.7	0.217	0.164	0.127	0.101	0.081	0.066	0.054	0.045	0.037
0.8	0.384	0.326	0.281	0.247	0.218	0.194	0.174	0.157	0.142
0.9	0.636	0.591	0.553	0.522	0.495	0.471	0.45	0.431	0.413
0.95	0.802	0.774	0.751	0.731	0.713	0.696	0.681	0.668	0.655
0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999

Table 1 – Exact values for cycle overflow probability P_o
(numerical results obtained by Markov Chain)

The exact values of P_o can be calculated numerically (Table 1 and Figure 1) using a Markov Chain (Wu, 1990). Compared to these exact values, eq. (5) (or eq. (11)) has a standard deviation $s = 0.00077$ and eq. (1) (or eq. (10)) has a standard deviation $s = 0.00098$. Thus, eq. (5) (or eq. (11)) is slightly better than eq. (1) (or eq. (10)) fitting the theoretically exact values.

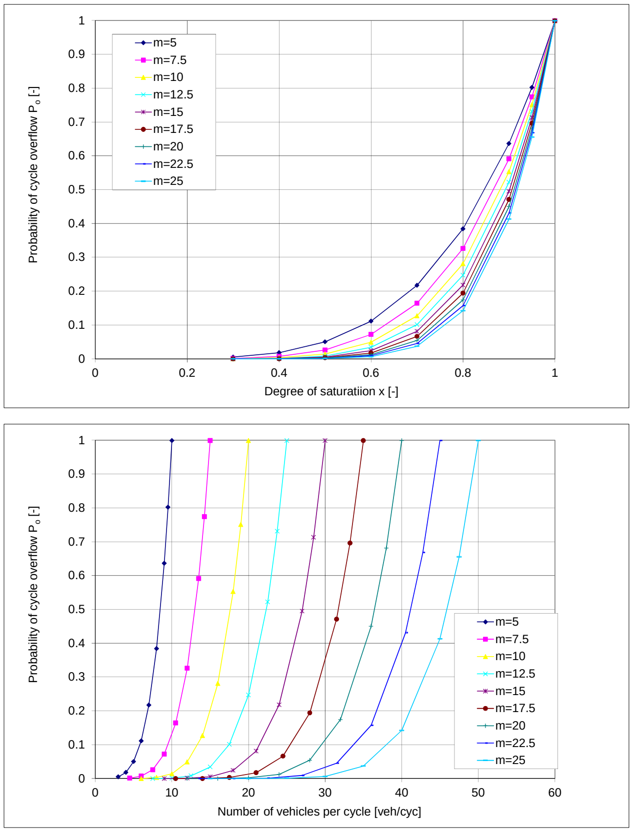

Figure 1 : top: P_o as a function of degree of saturation x; bottom: P_o as a function of number of vehicles per cycle n; legend: capacity of a cycle m

2.2 Estimation of Model Parameters

Using eqs. (10) and (11), the capacity per cycle m and the parameter a (or A) can be estimated by measuring the values of the probability of cycle overflow P_o and the demand per cycle n from detectors at stop-lines. In the practice, the probability of cycle overflow P_o can be defined as the proportion of the number of cycles with fully occupied detector during green phases to the total number of cycles. In the practice, the on-site detector has to be calibrated for measuring the probability of cycle overflow P_o beforehand.

Eq.(10) can be linearized as follows.

$$\ln(P_o) = -A\sqrt{m}\cdot\left(\frac{m}{n}-1\right) = -A\sqrt{m}\cdot\frac{m}{n} + A\sqrt{m}$$

Using P_o as independent and n as dependent parameter is

$$\frac{1}{n} = \frac{\ln(P_o)}{-A\sqrt{m}\cdot m} + \frac{1}{m} \qquad (12)$$

This equation delivers more accurate results for estimating the capacity per cycle *m* and it is preferred for further applications. That is, for estimating the capacity *m*, the following linear function is utilized.

$$Y = C_1 X + C_0 \tag{13}$$

with

$$\begin{aligned} Y &= \frac{1}{n} \\ X &= \ln(P_o) \\ C_0 &= \frac{1}{m} \\ C_1 &= \frac{1}{-A\sqrt{m}\cdot m} \end{aligned} \tag{14}$$

The coefficients C_0 and C_1 of the linear equation can be estimated using a linear regression model. Then, the capacity per cycle *m* and the parameter *A* can be calculated as

$$m = \frac{1}{C_0} \quad \text{and} \quad A = \frac{1}{-C_1\sqrt{m}\cdot m} \tag{15}$$

Eq.(11) can be linearized as follows.

$$\ln(P_o) = a\sqrt{m}\left[\ln(m) - \ln(n)\right] = -a\sqrt{m}\ln(n) + a\sqrt{m}\ln(m)$$

Using P_o as independent and *n* as dependent parameter is

$$\ln(n) = \frac{\ln(P_o)}{-a\sqrt{m}} + \ln(m) \tag{16}$$

That is,

$$Y = C_1 X + C_0 \tag{17}$$

with

$$\begin{aligned} Y &= \ln(n) \\ X &= \ln(P_o) \\ C_0 &= \ln(m) \\ C_1 &= \frac{1}{-a\sqrt{m}} \end{aligned} \tag{18}$$

Again, the coefficients C_0 and C_1 of the linear equation can be estimated using a linear regression model. Then, the capacity per cycle *m* and the parameter *a* can be calculated as

$$m = \exp(C_0) \quad \text{and} \quad a = \frac{1}{C_1\sqrt{m}} \tag{19}$$

In Figure 2, the linearized relationships between *n*, *m*, and P_o are illustrated for both eqs. (10) and (11). It can be seen, that by eq. (10) with higher values of capacity per cycle *m* the curves cannot be distinguished clearly. This fact could induce higher inaccuracy of estimated parameter *m*.

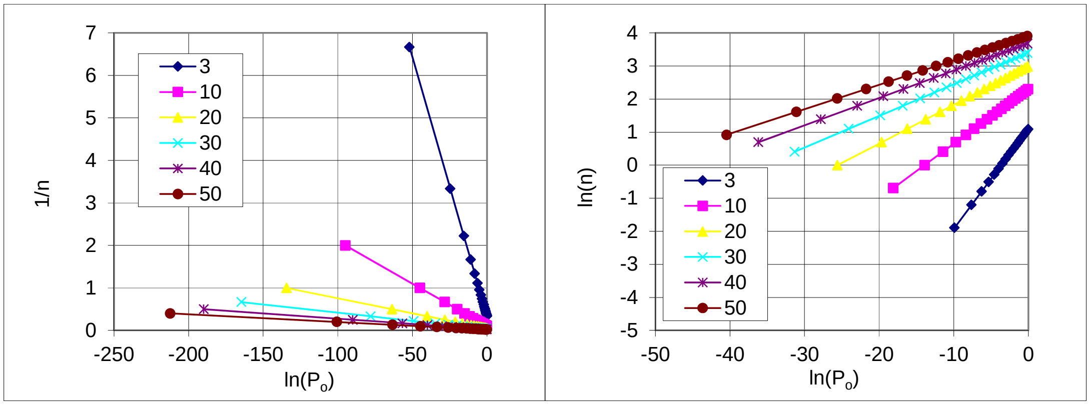

Figure 2 : left: linearized data for Miller's model (eq. (10)); right: linearized data for Wu's model (eq. (11)); legend: capacity of a cycle *m*

In the reality, the cycle time c and the green time g can be measured as well. Thus, the saturation flow rate s and the capacity C can be calculated as follows.

$$s = \frac{m}{g} \quad \text{[veh/s]} \quad \text{and} \quad C = 3600\frac{sg}{c} = 3600\frac{m}{c} \quad \text{[veh/h]} \tag{20}$$

3 Regression Studies and Sensibility Analysis

3.1 Regression Analysis

For demonstrating the regression results and the sensibility of the proposed approach, several regression studies are conducted. For estimation of capacity, the traffic demand or the degree of saturation has to vary in a certain range in order to conduct the regression. The conducted regression uses values for x = 0.6 - 0.95 with all together 8 data points (incremental step x = 0.05) and additional randomized values (standard deviation = 0.1*mean) for n and m as input parameters (cf. Figure 3) in order to simulate inaccuracy of measurements.

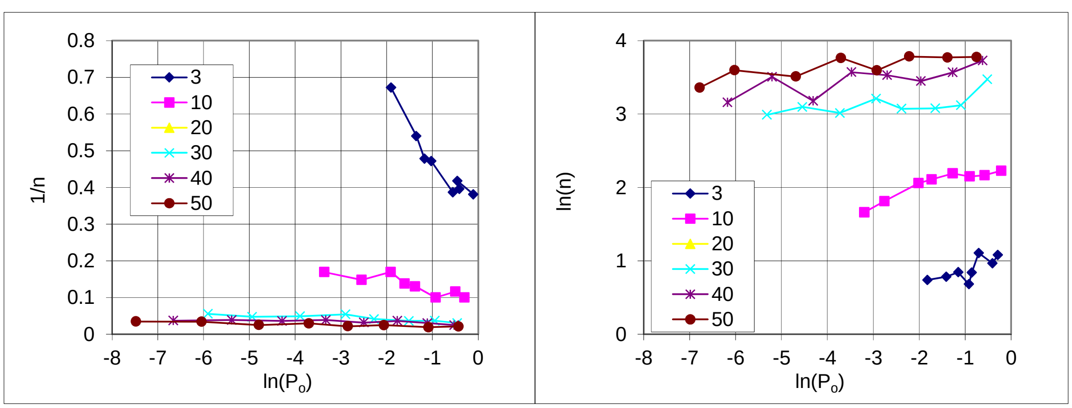

Figure 3 : left: randomized linear data from (10); right: randomized linear data from (11) (data range: x = 0.6 - 0.95); legend: capacity of a cycle *m*

Data no.	m=3	m=10	m=20	m=30	m=40	m=50	
1	3.16	9.27	19.9	31.00	34.90	47.90	
2	3.20	10.04	19.10	32.35	35.88	45.47	
3	3.33	10.01	20.25	28.83	34.64	47.83	
4	3.12	8.78	17.99	33.57	42.50	49.88	
5	2.94	9.19	19.78	31.54	35.86	50.83	
6	3.16	9.89	18.91	31.28	38.45	49.40	
7	3.11	8.86	20.70	30.68	42.87	49.63	
8	3.24	8.67	19.24	29.35	35.52	45.13	
9	2.81	8.95	17.85	38.94	48.03	54.79	
10	2.91	9.48	18.77	34.65	40.46	57.53	
11	3.04	9.96	18.21	33.33	40.06	48.64	
12	3.19	10.55	19.02	30.60	38.10	49.05	
13	2.76	11.00	21.00	28.37	44.23	46.90	
14	3.14	10.50	23.26	33.13	41.00	42.78	
15	2.72	9.51	18.12	30.41	39.96	45.38	
16	2.68	9.69	18.87	28.37	43.05	60.15	
17	3.12	8.82	17.76	27.12	37.77	52.70	
18	2.98	10.41	20.51	33.29	39.36	54.49	
19	2.63	11.25	21.80	35.65	42.60	44.26	
20	3.22	10.59	18.56	26.98	40.86	51.49	
Estimation	3.02	9.77	19.48	31.47	39.80	49.71	s
Input	3	10	20	30	40	50	1.07

Table 2 – Values of parameter *m* obtained from eq. (10) (data range: x = 0.6 - 0.95)

Data no.	m=3	m=10	m=20	m=30	m=40	m=50	
1	2.96	9.67	18.72	27.68	36.65	47.68	
2	2.97	10.22	15.05	29.51	36.57	47.11	
3	2.73	8.68	19.90	27.19	40.24	46.69	
4	3.00	10.24	21.07	31.66	42.11	50.69	
5	2.97	10.14	18.36	30.85	41.61	50.89	
6	3.00	9.23	17.95	31.60	37.94	46.66	
7	2.45	10.09	18.97	24.63	36.39	57.53	
8	2.83	10.68	21.80	28.23	36.44	52.42	
9	2.91	12.03	19.22	28.49	41.83	45.44	
10	3.33	9.68	18.55	30.41	40.43	47.47	
11	2.74	9.75	21.34	28.75	41.81	46.03	
12	3.02	10.75	18.75	29.67	43.53	54.65	
13	3.10	9.22	20.63	29.13	42.10	52.15	
14	2.75	9.23	20.72	30.03	43.59	46.81	
15	3.26	10.22	18.98	26.83	34.33	48.53	
16	2.90	9.42	19.85	29.42	43.17	44.31	
17	2.80	10.00	19.17	29.57	42.83	54.72	
18	3.05	10.52	18.70	30.64	45.25	45.97	
19	2.76	8.80	20.52	29.96	37.93	52.40	
20	3.17	10.03	20.21	29.34	38.14	50.49	
Estimation	2.94	9.93	19.42	29.18	40.14	49.43	s
Input	3	10	20	30	40	50	0.55

Table 3 – Values of parameter *m* obtained from eq. (11) (data range: x = 0.6 - 0.95)

The results of altogether 20 regression studies are illustrated in Table 2 and Table 3. It can be seen, that the variation of estimation is evident in the conducted 20 estimations. However, the average result of eq. (11) (standard deviation s = 0.55) is better than eq. (10) (s = 1.07) for reproducing the capacities m. The estimated value of a (=2.27) and A is (=1.71) are larger than the input data (1.77 and 1.58). That means the randomization of values for n (demand) and m (capacity) leads to a change of stochastic characteristics of the queuing system under consideration.

In Figure 4, the accuracy of the estimated results is illustrated together in dependence of the value of cycle capacity m. It can be seen, that the deviations are very small. The deviation in estimating cycle capacity m is a direct result of randomized input values of n (demand) and m (capacity).

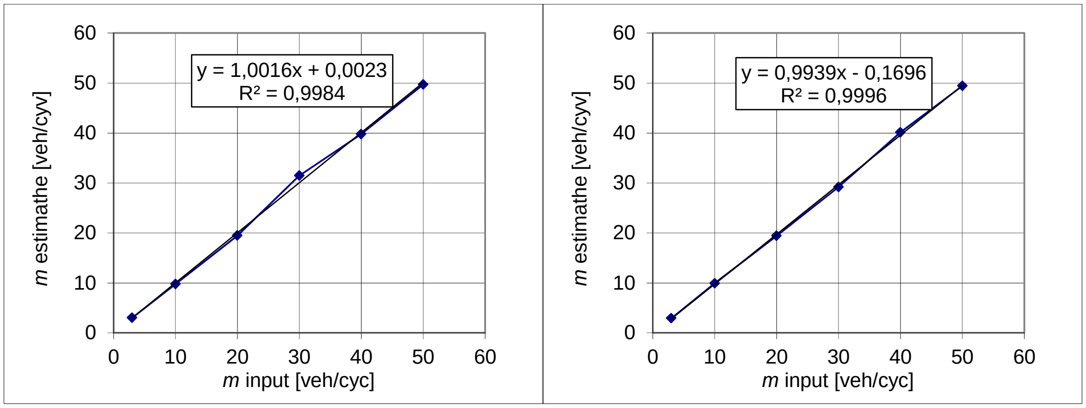

Figure 4 : Comparison of estimated and input data for the cycle capacity m
left: results from eq. (10); right: results from eq.(11)
(data range: x = 0.6 - 0.95)

According to the conducted sensitivity analysis, eqs. (11) and (10) deliver almost the same results. However, eq. (11) is relatively simple and robust. Thus, eq. (11) and its corresponding derivations (eqs. (17) through (20)) are recommended for capacity estimation at signalized intersections.

4 Possibility of Practical Applications

First of all, the proposed model can be used for generating a database of saturation flow rates using historical or online detector data with respect to different geometrical and traffic conditions such as geometric design of intersections, proportion of heavy vehicles, time interval under consideration, weather influence, and so on.

For on-line applications the model can be combined with other techniques such as Flying Windows, Smoothing, Rolling Regression, or Kalman Filter (cf. AIDA, 2000; Bernhard and Riedel, 1999; Friedrich, 1999, 2000; Mück , 2001; Papageorgiou, 1991; Wu, 2004).

For capacity estimation, the model is also applicable for data from oversaturated situation and from actuated or coordinated traffic signals. The model has the capability to estimate the stochastic characteristics of the queueing systems for actuated or coordinated traffic signals. For calculating delays and queue lengths under unsaturated situations, the estimated queue length at end of green time N_{GE} (eq. (2) or eq.(6)) can be used directly (cf. eq. (9)). This applies also to actuated and coordinated traffic signals.

5 Application Examples with Simulation Data

To examine the capability of the proposed model, a comprehensive VISSIM simulation study is conducted. The simulation is carried out for a two-lane approach using different input parameters depicted in Table 4. The duration of the simulations is 10 hours for any input dataset. The last 9 hours are used for the regression calculations while the first hour serves as a preload of the system.

		c=60s		
		q [veh/h]		
Data no.	x (for s=0.56 veh/s)	g=10s	g=20s	g=30s
1	0.6	400	800	1200
2	0.7	467	933	1400
3	0.8	533	1067	1600
4	0.9	600	1200	1800
5	0.95	633	1267	1900

Table 4 – Input data of the simulation study

In the simulation study, detectors are placed direct at the stop-lines for both lanes separately. The detectors register each second of occupancy. If every second of green time is occupied, the cycle is considered as overloaded. The cycle overflow probability P_o is then calculated as the proportion of number of overloaded cycles to number of all cycles under consideration. The number of passing vehicles per cycle n can be counted directly by the detectors as well.

			c=60s					
.			g=10s		g=20s		g=30s	
Data no	x (for s=0.56 veh/s)		P_o	n	P_o	n	P_o	N
1	0.6	lane 1	0.1352	3.24	0.0111	6.38	0.0010	9.47
		2	0.1241	3.22	0.0093	6.43	0.0010	9.51
2	0.7	lane 1	0.2500	3.84	0.0333	7.37	0.0093	10.90
		2	0.2370	3.80	0.0370	7.39	0.0093	10.92
3	0.8	lane 1	0.3519	4.22	0.1130	8.37	0.0370	12.35
		2	0.3704	4.30	0.1148	8.37	0.0463	12.34
4	0.9	lane 1	0.5074	4.71	0.2259	9.35	0.1167	14.06
		2	0.5056	4.76	0.2259	9.35	0.1167	14.05
5	0.95	lane 1	0.6093	5.09	0.3167	9.78	0.1704	14.55
		2	0.6259	5.03	0.3148	9.75	0.1926	14.56
6	m in saturated cycles		5.53		11.36		17.16	
	corresponding s (veh/s)		0.55		0.57		0.57	
7	estimated m		5.81		11.24		17.05	
	corresponding s (veh/s)		0.58		0.56		0.57	
8	estimated a		3,50		8,21		12,01	

Table 5 – Results for the simulation study

The results of the simulation study are illustrated in Table 5 and Figure 5. By the simulation, numbers of vehicles during saturated cycles are counted separately. These numbers (no. 6 in Table 5) can be considered as the capacity because all cycles used here are saturated. This capacity can be used as a counter-check for the estimated capacity under unsaturated conditions (datasets no 1 through 5).

The two estimated capacities are not identical but comparable (cf. dataset no.6 vs. dataset no.7 in Table 5).

The estimated values of parameter *a* (cf. dataset no.8 in Table 5) are much larger than the model value (1.77 for eq. (11)) for the theoretical M/Bunch/1 queuing system. Larger values of parameter *a* mean the simulated traffic flow at signalized intersections is less random than the predefined M/Bunch/1 queuing system. The value of parameter *a* depends on the green time *g*, thus on the cycle capacity *m*. Obviously, the Markovian assumption doesn't apply for the input process at real intersections. In addition, at double lane approaches, the traffic flow at any single lane is less random because vehicles can chose the lane before the stop line if the input flows of both lanes are imbalanced. Furthermore, the real traffic flow gets more and more bunched with increasing flow rate because vehicles must maintain minimum time headways in between. All of the effects reduce the randomness of input flow.

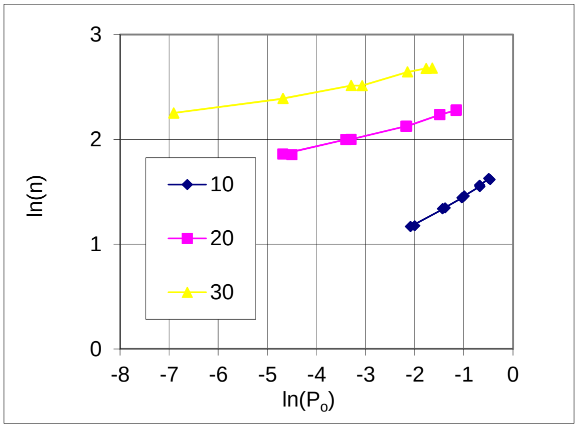

Figure 5 : Simulated data for $P_o = f(n, g)$; legend: green time *g* for the simulation

6 Conclusions and Outlook

Based on the queue theory at signalized intersections, relationships between capacity and stochastic characteristics of signalized intersections are investigated. It can be seen that the capacity and the characteristics of signalized intersections can be estimated by measuring the cycle overflow probability. The model is validated and verified by a simulation study. For demonstrating the ability and applicability of the model a sensitivity analysis is conducted. Two basic queue approaches are tested for the proposed model. It turns out, that both models can reliably estimate the capacity at signalized intersections. However, eq. (11) is relatively simple and robust. Thus, eq. (11) and its corresponding derivations (eqs. (17) through (20) are recommended for capacity estimation at signalized intersections. Then, eq. (8) can be used for calculating queue lengths at end of green time and eq. (9) for calculating delays at unsaturated intersections with traffic signals.

In the next step, an investigation will be conducted applying the model to on-line collected data at real intersections (fixed-time, actuated or coordinated) in order to estimate the variation of capacities and delays and to investigate the stochastic characteristics of the queueing systems for actuated or coordinated signals.

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