CAPACITY OF CURBSIDE BUS STOPS LOCATED ON BUS CORRIDORS, CONSIDERING LEVEL OF SERVICE, OVERTAKING LANES AND A DOWNSTREAM TRAFFIC SIGNAL

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ABSTRACT

The frequency of buses that a curbside bus stop can serve does not only depend on variables like dwell time or available berths. Several other external traffic conditions may also affect bus stop capacity. Furthermore, the capacity should be associated to an expected delay (or level of service) suffered by buses when they approach the stop. This study proposes a new model for estimating the capacity of curbside bus stops on bus corridors, which measures this level of service using queue time as a metric. The model also examines the effects of overtaking lanes and downstream traffic light. It is shown here that an overtaking lane increases bus stop capacity by 9%, while a downstream traffic light may decrease it between 17% and 48%, depending on the distance to the bus stop. This study should allow transit agencies to make better decisions designing bus corridors, including the number of berths per station, the location of bus stops along a street block, or the implementation of overtaking lanes.

Keywords: Bus stop capacity, Queue time, Downstream traffic light, Overtaking lane.

1 INTRODUCTION

Surface public transport faces three delay sources: street traffic, traffic lights, and dwell time at bus stops (*1*). While street traffic and traffic lights can be considered external sources of delay, public transit agencies can intervene bus stop design and operations affecting bus delays. The time a bus spends at a stop can be separated into four components. The first, known as queue time, is the amount of time a bus waits before reaching the berths and passengers start boarding and alighting. The second, known as dwell time, is the amount of time the bus waits for passengers to board and alight. The third, known as acceleration and deceleration time, is the amount of time the bus needs to stop at the bus stop, and subsequently, to pull away from it. The fourth, known as internal waiting time, occurs when one bus blocks another due to a downstream traffic light. While dwell time and deceleration and acceleration are part of a bus's normal operation, queue time and internal waiting time are excess delays that not only damage travel times and regularity, but can also cause problems at upstream intersections. In this paper, this delay is referred to as the *level of service* received at the stop. Buses are affected by queue time when their frequency assigned to a bus stop approaches its capacity, and bus stop capacity is affected, in turn, by internal waiting time. Thus, predicting the number of buses that a stop can actually serve requires understanding the impact of queue time, internal waiting time, and delays caused by downstream traffic lights.

This study proposes a model for estimating the capacity of curbside bus stops in segregated bus corridors. This model incorporates the impact caused by external conditions like overtaking lanes and downstream traffic lights. The model predicts the amount of buses that can be served at a stop for a given level of service associated to the bus stops' operational design.

The following section presents a review of the literature on techniques for estimating bus stop capacity. Section 3 outlines the model and the data used within it, along with its estimation results. A practical application of the model to the segregated bus corridor on Vicuña Mackenna Avenue in Santiago de Chile is shown in Section 4. Finally, conclusions and topics for future research are presented in Section 5.

2 LITERATURE REVIEW

The estimation of bus stop capacity has been widely discussed in transportation literature. Analytical models like the one presented in *The Highway Capacity Manual (HCM)* (*2*) - and replicated in the *Transit Capacity and Quality of Service Manual* (*3*) - estimate bus stop capacity assuming that buses arrive at regular intervals. In addition to variables such as clearing time, dwell time and number of berths, this model incorporates the level of service and the presence of a downstream traffic light. Service level is measured using the probability, or *failure rate (FR),* that berths are already occupied when a bus reaches a bus stop. Even though the *FR* is a metric used in professional handbooks (e.g., (*2*), (*3*)), it does not quantify impacts on time the way a metric based on queue time can. Although intuition might suggest that maximum capacity is reached when there is a permanent queue of waiting buses (*FR* = 1), this formula estimates that the maximum capacity occur at *FR* = 0.5. Gu et al. (*4*) question the marginal increase of capacity estimated by the *HCM* model when more berths are added. Furthermore, the influence of downstream traffic lights is estimated using the proportion of the time that a light is green, with respect to the cycle as a whole. However, intuition suggests that the effect of downstream traffic lights is due not only to timing, but also to the distance between the light and the bus stop. This effect is due to the possibility that one or more buses may accumulate between the light and the stop – a possibility not included in the formula. While this formula is valuable for its pragmatism, some authors have questioned its usefulness. Gibson et al. (*5*) mention that it is too simple to take the wide variety of operating conditions, or the complexity of stochastic bus arrival processes, into account. In addition, Fernandez and Planzer (*6*) claim that the formulas tend to underestimate bus stop capacity when compared to other field studies.

Bus stop operation simulation software have also addressed the problem of capacity estimation. These software allow users to model different operational conditions more realistically, and address the main concerns inspired by models like that of the *HCM*. Gibson et al. (*5*) present a simulation program call IRENE that analyzes bus stop capacity, queue time, dwell time and bus stop berth use. Input variables include passenger boardings and alightings, the number of berths, bus size, and the randomness of arrivals. In a later version of the same program, Gibson (*7*) adds a variable indicating the presence of a downstream traffic light, which is modeled both with timing and with the distance to the bus stop. Fernandez (*8*) presents a simulation software called PASSION that delves more deeply into the impact that random passenger arrivals have on waiting time and congestion at bus stops. It also allows a user to define different routes of public transport that can have heterogeneous demand, unlike IRENE, which allows for only one route. Despite including four different types of bus stop exits (free, blocked, controlled by a traffic light, and through adjacent gaps in traffic), these cannot be combined. Moreover, the downstream traffic light is allowed to affect outcomes only through the timing of green lights, and not through its distance to the bus stop. The capacity of bus stops estimated by IRENE and PASSION are similar in magnitude (*9*). However, this estimated capacity is theoretical, since calculations require saturated bus stops -- which does not correspond to the reality of standard service levels. Therefore, authors of these models estimate practical capacity to be 60% of the calculated theoretical capacity. This definition would indicate a baseline of less than one bus in queue 50% of the time, and an average waiting time of less than 60 seconds per bus. While it is true that these software produce quite accurate estimates, they all make use of computational simulation tools to some degree (*10*), which discourages their use in models with a large number of bus stops.

Recently, transportation scholars have introduced different models in an attempt to strengthen previous analyses. Gu et al (*4*) present an analytical model which includes service level with the *FR* metric for three bus arrival distributions: Poisson, Uniform and Erlang. This analysis presents interesting insights as to the effect that reducing dwell time variation can have on bus stop capacity. It also illuminates the reductions in bus stop capacity due to bus arrival randomness, and calculates the marginal return of adding additional berths in these cases. Gu et al. (*10*) develop a model using Markov chains to estimate the maximum arrival and response rate of buses, taking level of service into account, measured as the average delay time. This model shows that, for any value of average delay time, productivity decreases as the coefficient of variation of dwell time increases. Furthermore, these authors compare average delay and *FR* metrics, showing that the same *FR* standard matches different average delay times and for different numbers of berths. That is, reductions in average delay due to additional berths cannot be captured by models using *FR*. Despite their useful results, both (*4*) and (*10*) only analyze cases where stops are isolated from the influence of traffic lights, and do not allow overtaking.

3 MODEL

This section presents the data used to estimate the model, its specification and results.

3.1 Data

Queue time data come from simulations of 720 scenarios representing different bus stop operating conditions. Each scenario is replicated 100 times in IRENE, Version 4.2 (*7*), to obtain the average queue time.

This study has several assumptions. First, it is assumed that buses use segregated bus corridors, thus avoiding the influence of other vehicles as in mixed traffic. Buses reach the stop at random times drawn from a negative exponential distribution (*11*), which is realistic when bus regularity is not well-controlled, or when buses from different routes use the same bus stop. It is also assumed that, to load and unload passengers, buses use the most downstream available berth in the stop, and that buses always have capacity. Boardings and alightings are assumed to be distributed evenly on each bus, which establishes an average dwell time with low variability (i.e., coefficient of variation ≈ 0). Also, bus stop exits may be blocked by buses at downstream berths or by a downstream traffic light. When a traffic light is present downstream, it is assumed that it will be green for 50% of its cycle time. Overtaking lanes are another operational factor taken into account by the simulation model, and cases with and without overtaking lanes are modeled. When there is an overtaking lane, buses that have finished the boarding and alighting process can pass those that are at downstream berths.

Each scenario has different bus frequencies (between one and 250 buses per hour), and different average dwell time (between zero and 60 seconds per bus). The bus stop is modeled with one and two serial berths. Two types of buses are considered: rigid and articulated, measuring 12 and 18 meters respectively. These are different not only because of the space they take up, but also because of their different saturation flow.

Downstream traffic lights are incorporated in the model by considering their distance from the bus stop. Greater distances allow more buses to accumulate between the light and the bus stop, but preliminary results show that if the light is farther than 40 meters the stop behaves as if it was totally isolated. The distances considered in the process were linked to the number of large buses (18 meters) fitting between the light and the bus stop without affecting the bus stop performance. Four categories were considered: isolated, 40 meters (or 2 buses), 20 meters (or 1 bus), and 10 meters (no buses).

3.2 Model Estimation Results

A regression model is estimated in which queue time is the endogenous variable. This is generally recognized to behave nonlinearly with respect to key inputs as the bus frequency. Its generic functional form resembles the exponential distribution, although literature still contains few efforts to empirically estimate queue time at bus stops (*12*, *13*, *14*).

The calibrated model must fit the data, and the sign of each parameter must make sense in the context of the relation between queue time and the respective variable. Intuition suggests that, as bus frequencies get higher and dwell time longer, queue time ought to increase. On the contrary, a greater number of berths increases bus stop capacity and therefore should reduce queue time. Larger buses have lower saturation flow rates, and this probably contributes to increments in queue time. Also, the presence of a downstream traffic light increases internal waiting time, which should, in turn, increase the queue time. This ought to occur in greater magnitude if the light is closer to the bus stop. Finally, the presence of an overtaking lane should reduce queue time, since internal waiting time decreases. In sum, the sign of the parameters associated with these variables must coincide with the ones shown in Table 1.

TABLE 1 Variables, Parameters and the Expected Sign in the Estimation Model

Variable	Parameter	Sign
f_b : Frequency	β_{fb}	(+)
t_d : Dwell time	β_{td}	(+)
n : Number of berths	β_n	(-)
l_b : Bus size	β_{lb}	(+)
s_{0b}: Downstream traffic light at close proximity	β_{s0b}	(+)
s_{1b}: Downstream traffic light 1 bus length away	β_{s1b}	(+)
s_{2b}: Downstream traffic light 2 bus lengths away	β_{s2b}	(+)
o_l : Overtaking lane	β_{ol}	(-)

The variables for number of berths (n), overtaking lanes (o_l), and downstream traffic light distances (s_{0b}, s_{1b}, s_{2b}) are dummies. For example, when n, o_l, s_{0b}, s_{1b} and s_{2b} equal zero, this means that the bus stop has one berth, no overtaking lane, and no downstream traffic light.

Equation (1) shows the functional form of the model that explains average queue time (t_q), depending on the variables presented in Table 1.

$$t_q = m \cdot e^{p \cdot f_b} \tag{1}$$

The terms m and p represent the interaction between dwell time, number of berths, bus size, downstream traffic lights, and the overtaking lane. Model parameters are estimated with the *Levenberg-Marquardt algorithm*, using the SPSS nonlinear regressions package (version 20). This procedure is identical to that used in (*14*).

Table 2 contains parameter estimates and their significance for the best-fitting model, which remain consistent with intuition. This model includes m and n, as presented in Equations (2) and (3).

$$m = 0{,}001 \cdot (\beta_1 + (\beta_{td1} + (\beta_{s0b} \cdot s_{0b} + \beta_{s1b} \cdot s_{1b} + \beta_{s2b} \cdot s_{2b}) + (\beta_{n1} \cdot n)) \cdot t_d) \tag{2}$$

$$p = 0{,}001 \cdot \left(\beta_{fb} + (\beta_{td2} + \beta_{n2} \cdot n + \beta_{ol} \cdot n \cdot o_l) \cdot t_d\right) \tag{3}$$

TABLE 2 Parameter Estimates and Significance for the Chosen Model

Parameter	Estimate	Standard Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
β_1	-43.44	17.11	-77.03	-9.85
β_{td1}	141.49	17.39	107.33	175.65
β_{s0b}	134.24	10.91	112.83	155.65

β_{s1b}	66.10	6.93	52.49	79.72
β_{s2b}	26.71	3.80	19.25	34.17
β_{n1}	-105.48	16.65	-138.16	-72.79
β_{fb}	21.14	0.41	20.33	21.95
β_{td2}	0.76	0.06	0.64	0.88
β_{n2}	-0.21	0.06	-0.34	-0.09
β_{ol}	-0.16	0.02	-0.19	-0.13

From the table, it can be seen that the signs of the parameter estimates align with intuition. It is also worth noting that the effect of a downstream traffic light decreases as the distance from the bus stop increases. Also, the dummy for the overtaking lane is only statistically significant when interacted with the number of berths. It does not make sense to pass a downstream bus when there is only one berth and all the buses have to serve the bus stop being blocked. On the other hand, bus size was tested with various different functional forms, but this parameter was not significant. As is mentioned above, smaller buses have higher saturation flow rates. Nevertheless, this variable had no significant effect on queue time.

While this paper provides a model relating the average queue time with the variables listed above, the main goal is to construct a model for bus stop capacity. This capacity is directly linked to queue time. The capacity of a bus stop grows if the threshold for maximum queue times at the stop grows. Thus we define the practical capacity not as the theoretical value obtained when all berths are occupied 100% of the time. Instead, the practical capacity will be given by the quantity of buses a stop can effectively handle, while maintaining an acceptable level of service. Clearing the frequency variable of the model expression in Equation (1) results in Equation (4). This indicates the rate of buses that can be served by the bus stop under certain operating conditions and with a standard average queue time. This frequency can be interpreted as the practical capacity of the bus stop (C_b).

$$C_b = \frac{\ln t_q - \ln m}{p} \tag{4}$$

Figure 1 shows practical bus stop capacity as a function of dwell time, for four operational configurations. The black line (i) and the red line (ii) represent isolated bus stops with and without overtaking lanes, respectively. The green line (iii) and the blue line (iv) represent bus stops with downstream traffic lights and no overtaking lanes; the first traffic light is two bus lengths away and the second is directly downstream. If the case in which a bus stop is isolated and has no overtaking lane (i.e. case i) is considered as a reference, isolated bus stops with overtaking lanes (case ii) show smaller increases of capacity than the reductions that occur in cases with downstream traffic lights ((case iii) or (case iv)). For a typical dwell time of 15 seconds per bus, capacity is increased by 9% in the case of an isolated bus stop with an overtaking lane (case ii). When there is a downstream traffic light and no overtaking lane, capacity is reduced between 17% and 48%, in cases (iii) and (iv) respectively.

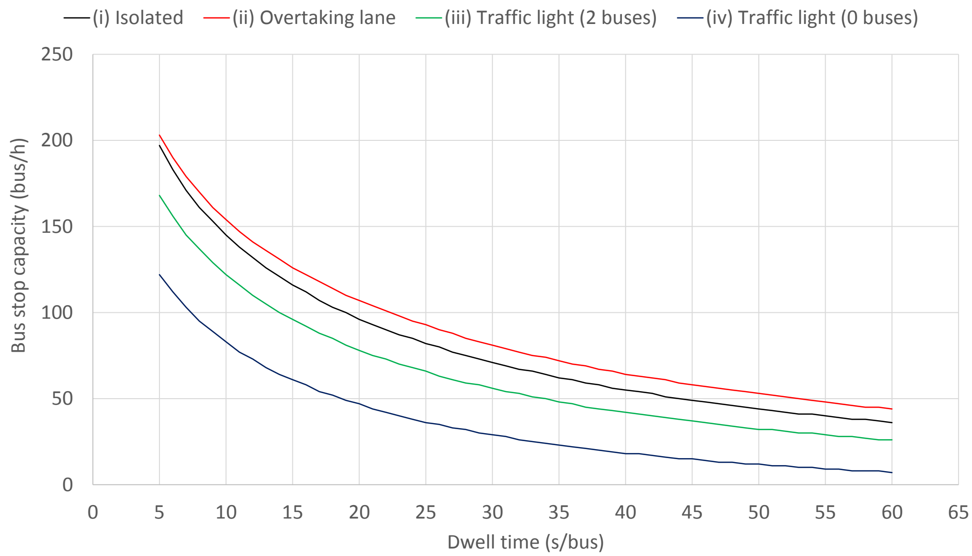

FIGURE 1 Bus stop capacity (i) isolated without an overtaking lane, (ii) isolated with an overtaking lane, (iii) with a traffic light two bus lengths downstream and without an overtaking lane, and (iv) with a traffic light immediately downstream and no overtaking lane, assuming two berths and an average queue time of 15 seconds per bus.

4 APPLICATION

The model has been applied to the 31 bus stops along the segregated bus corridor on Vicuña Mackenna in Santiago de Chile. The stretch of road is 5.17 km long, with lanes going in both directions.

The data from the ADATRAP software (*15*), include information for passengers alighting and boarding every half hour in each service and each bus stop for one week of 2014. Based on this information the dwell time (t_d) at each stop can be inferred. The dwell time can be assumed to be a sequential or a simultaneous process. Bus stops with pre-payment stations have sequential alighting and boarding processes, as shown in Equation (5), while bus stops where payment occurs on the bus operate with simultaneous processes, as shown in Equation (6).

$$t_d = c_1 + a_1 \cdot A + b_1 \cdot B \tag{5}$$

$$t_d = c_2 + max\{a_2 \cdot A; b_2 \cdot B\} \tag{6}$$

The variables A and B represent the number of passengers boarding and alighting, respectively, and a_i, b_i and c_i are constants (depending on the bus stop configuration *i*). The "dead time" term, which is the constant c, represents the time required to open and close the doors, and for the driver to check that everything is in order before leaving. The terms a and b represent alighting and boarding times respectively, in seconds per passenger. The values for c, as well as a and b, are obtained from estimates from the Santiago context (*16*).

The dummy variables representing the presence of downstream traffic lights on Equations (2) and (3) (s_{0b}, s_{1b}, s_{2b}) are derived from geo-referenced bus stops and traffic lights in Santiago. This enables the determination of whether the traffic light is located upstream or downstream of the stop, as well as the distance between the two.

The segregated bus corridor profile does not have overtaking lanes. Since no information is available on the number of berths, it is assumed that all bus stops have two berths available for service. The level of service defined for the queue time in this analysis is set at 10 seconds per bus. Using this information we can compute the practical capacity of each stop in the corridor through expressions (2), (3) and (4).

The saturation for each bus stop is then calculated as the ratio between the planned frequency and the practical capacity, as estimated by the model (f_b/C_b). The periods analyzed were morning and evening rush hours. Figure 2 shows the saturation histogram of Vicuña Mackenna's segregated bus corridor.

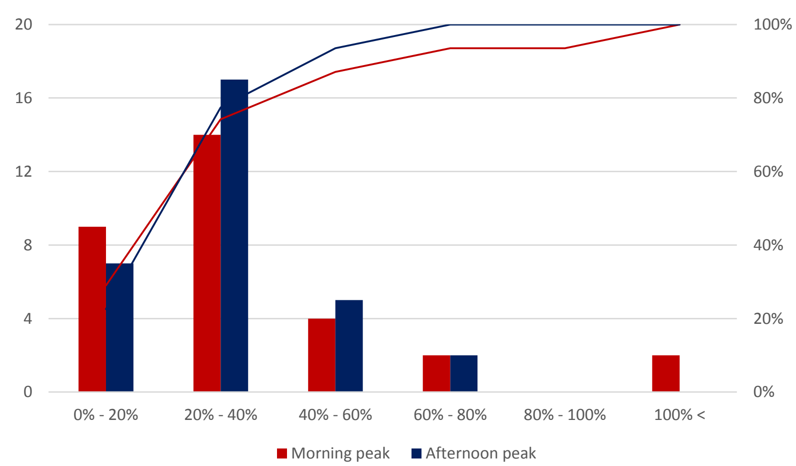

FIGURE 2 Bus stop saturation histogram along Vicuña Mackenna's segregated bus corridor.

Saturation is less than 80% for 94% of bus stops in peak morning hours, and 100% of bus stops during peak evening hours. However, two stops show saturation greater than 100% during the morning rush hour. This is indicative that these stops have a queue time higher than 10 seconds. If pre-payment stations were put in place at these bus stops, dwell time would decrease, resulting in new saturation indicators of 54% and 106%. The bus stop that remains oversaturated in this scenario is situated at the end point of the segregated bus corridor, which is mostly used by riders who transfer to Metro after alighting from buses at this stop. In addition, a traffic light located two bus-lengths downstream decreases capacity. For these reasons, the implementation of a pre-payment station is not enough to solve the oversaturation problem in this particular bus stop; other measures should be applied.

5 CONCLUSIONS

The bus stop capacity model proposed in this paper has two key characteristics that differentiate it from others available in the literature. The first difference is that average queue time is incorporated into the formula of the model as a variable, which allows for the establishment of a standard level of service, defining a bus stop's capacity. Unlike other metrics, the average queue time variable allows the quantification of the effect of these bus stops on users' travel time and also on costs to the operating companies. The second difference is that the model includes the effect of overtaking lanes and downstream traffic lights in its capacity calculations. Overtaking lanes have limited effects, but downstream traffic lights can have a considerable influence on capacity, especially when the light is located immediately downstream. Both the general insights mentioned in this report and the model developed are tools that should contribute to the better planning of bus stops by public transport agencies.

For future research, it is worth noticing that the omission of a variable showing the influence of mixed traffic on a bus stop is a limitation of this work. The proposed model assumes that bus stops are located on segregated bus corridors, but an analysis of the influence of other vehicles on the road could be included. Another possible line of inquiry might consist of the loosening of some of the assumptions made, such as testing other distributions of bus arrivals, greater variance of stopping times, and different proportions of green lights in downstream traffic lights. Transportation literature already has contributions of this type, but these also simplify some of the variables analyzed in the present research.

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