Advances in Transportation Studies: an international Journal 57 (2022)

ISBN 979-12-218-0006-7 – ISSN 1824-5463 – DOI 10.53136/979122180006711 – pag. 159-170

Application of gamma models for off-peak dwell time in urban transit routes: a case of study in the Greater Metropolitan Area, Costa Rica

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subm. 16th June 2021 approv. after rev. 20th December 2021

Abstract

The dwell time at bus stops is affected by factors such as the number of passengers, the method of payment, the configuration of the buses, among others. Therefore, to find the necessary balance in public transportation, where the comfort of the users and the operational needs of transit agencies are the best, it is necessary to make an efficient route design and optimize the methods of payment and boarding. Generally, the analysis of this problem is carried out through multivariable regressions, either linear or non-linear, where the variables that are taken into account depend on the focus of each study. In this case, a generalized linear model is used, using the gamma distribution. The application of generalized linear models using the gamma distribution allowed the modeling of the phenomenon studied and determine the factors that significantly affect the stoppage time. It was determined that, when comparing the same type of bus and on the same route, the main factors that directly affect the bus stop time are the number of users, the method of payment and the configuration of the buses. By generating a general model, including all available data, it is possible to evaluate some of the parameters responsible for dwelling time variations. This allows to establish the effect when implementing the use of buses with low floor in this public service, obtaining a decrease of approximately five seconds in each stop that the vehicle makes along its route.

Keywords – alighting, boarding, dwelling time, generalized linear model, bus stop, transit

1. Introduction

Dwell time could influence total travel time [15], headway adherence and headway distribution [24] and could affect operating costs [23]. Dwell times have been used as a variable to predict travel time [1]. Additionally, the dwell time could be critical in the design of powered electric buses and bus stops [9]. To determine the quality and performance of transit systems it is essential to consider the time required by a bus to stop while passengers board or alight the bus, including also the doors' opening and closing times. This time interval has been defined as "dwell time" [30] and it can be analysed by segregating the total stop time into several components including, the time of boarding and the time of alighting for the passengers at each bus stop [18].

The passenger service time corresponds to the component that most influences the duration of each stop [30]. The Transit Capacity and Quality Service Manual [30] mentions the amount of passengers, the payment´s method, the type of bus, and the design of stops as the most relevant factors for dwell time. Clearly, understanding the effect of each of the mentioned factors will be of interest, in order to improve the performance of the public transportation systems, particularly in most modern cities where congestion is increasing rapidly.

To better understand the effect that these variables have on dwell time, several authors have proposed the use of regression models [6, 19, 21, 22]. However, previous studies have use mainly linear models that might produce biased estimates since dwell times are strictly positive and right-skewed. Transformations for positive right-skewed data such as log transformations can be used in time data such as dwell times but this approach has two main drawbacks: it can produce biased estimates in the face of heteroscedasticity if not appropriately retransformed [26] and this transformation implies that the effect of the covariates is multiplicative rather than summative as you will expect for dwell times (i.e. each person boarding or alighting adds to the dwell time).

The gamma distribution is suitable for data that are continuous, positive, and right-skewed. Given these characteristics, the gamma distribution is a good choice for describing dwell time since these times are always greater than zero, continuous and have an extended tail to the right of the distribution (right or positive skewed). Dwell times also frequently have high variability and low means which makes the gamma distribution ideal for modelling this type of data [14]. Also, gamma regression is suitable to work on the original scale of the analysed variable. Other approaches for skewed data such as log-transformation do not work in the original scale for estimation, while the gamma distribution has an expected value that can be expressed as a linear function of the covariates.

The purpose of this paper is to model dwelling time data using a gamma regression model. The contribution of this study is to apply a model that overcomes the heteroscedasticity typically present on dwell time models and to characterized dwell times in Costa Rica, since there is limited literature regarding dwell time in Latin-American. This paper is organized as follows: first, a review of the dwell time models proposed in the literature is presented; then, the methodology is introduced; next, the data are presented; then, the results are discussed, and finally, the conclusions and recommendations for future research are shown.

2. Literature review

Levinson [22] published one of the first articles on the importance of studying the dwell time in the public transport service. This study emphasizes that the travel times and the speed of operation of the buses influence directly the efficiency, costs and perception of service's users, confirming the importance of the dwell time because it represents approximately 26 % of the total travel time. In addition, a significant percentage of this time is the period when passengers board and alight, which makes it important to find the variables that most affect it. Despite the relevance of these factors, there were few studies related to the density of passengers, traffic conditions and land use [22] which until then had been carried out.

The average stop time that was obtained in the analysis was 30 s, and the maximum time estimated was 60 s. According to the results, a bus in the city has a longer stoppage time (15 s) than in suburban areas (10 s). At the end of his analysis, Levinson [22] concludes that boarding times depend mainly on the payment system. Similarly, he suggests that when making the payment before entering the bus, each passenger takes 1.5 to 2.5 s to board; if the payment is made at the time of entering the bus with a card, the time varies between 2 and 3 s. The longest time is when the payment is made with cash inside the bus; in this case, the range is 3 s and 4 s. For the same study, it is indicated that, the alighting times vary depending on the load that the passenger has, which is between 1.5 and 2.5 s when the passenger carries little hand luggage; and when the load is considered moderate, it can vary from 2.5 and 4 s.

York [33] conducted an investigation on dwell time, taking into consideration the variable of the payment method (passes, exact payment, requires change), in addition to the bus type (buses with a door, or two-door buses). The author establishes that, the average boarding time per passenger is between 1.6 and 8.4 s; the alighting time round of 1.1 s to 2.0 s per person. Additionally, it also estimates that the dead time, that considers the time it takes the doors to open and close, or any distraction that the driver may have, is between 2,8 s and 8.3 s.

In addition, Levine [21] studied the dwelling time, but in this case using low-floor buses, with the objective of identifying the effects that this new bus design would have on the system. The stop time was modelled by multiple regressions considering the type of bus, the number of passengers boarding and overflows, and the payment method used. As a result, they obtained that, on average, the stop time was 5 s less than the average a high-floor bus.

Similarly, Dueker et al. [4] present a dwelling time model taking into account the effect of a low-floor bus, obtaining a coefficient for this variable of -0.11 s per stop. A typical route, in which the analysis was carried out, on average the bus stopped at 60 % of the 60 stops of a journey; therefore, the reduction in the total travel time per journey corresponds to 3.96 s due to the low floor feature.

On the other hand, Puong [28] performed an analysis that evaluates the dwell time using a non-linear model, which was carried out in the "Red line", one of the four rapid transit lines of the Boston subway. The results showed that all the dwell times at the stops were less than 1.5 min. In addition, the movements of the passengers when getting on and off the train showed enough variation, so they used a least squares regression to analyse the information.

Additionally, Glick and Figliozzi [10] considered the bus stop location, and the speed, as a surrogate for level of congestion. They also considered users in wheelchair in their study. Similarly, [19] studied the presence of passengers with mobility aids on dwelling times. Additionally, Mahdavilayen et al. [25] used a mock bus to determine the effect of different boarding conditions on passengers on wheelchairs. Urazan et al. [32] classify the passengers in five categories: children, elders, users with packages, users with other cargo that difficult boarding the bus, and adults without packages or cargo. Kostyniuk and D'Souza [19] determined that passengers with mobility aids and encumbrances increase the dwell time.

Table 1 summarizes the main models obtained from the literature review, several of the models presented in the table have already been discussed; however, other models are also presented, due to the relevance that their results have had for this study.

A more recent study, completed in Sydney, Australia [31] collected stop-time information from low-floor buses, and buses with bleachers, and three different types of public transport services were analysed. The main difference obtained was related to the payment method (cash, prepaid card, and free). The analysis of the data was performed through linear regressions, and a model was obtained for each of the scenarios studied. The scenario where low-floor buses and buses with bleachers are analysed together, a new element was implemented that explained the increase in time due to the bleachers, which has a positive coefficient of 2.2 seconds per passenger.

Similarly, during the last few years, research has been completed regarding the bus boarding and unloading times, starting from tests in real-scale laboratories. An example of this is the study carried out by Fernández [7], in collaboration with the Movement Environment Laboratory (PAMELA) of University College London and the Digital Imaging Research Centre (DIRC) of the University of Kingston, London. The research focuses on three main variables, the height of the platform (0, 15 and 30 cm), the width of doors and the method of payment (payment outside the vehicle and payment by electronic card when boarding). For each value of the variables studied, 15 to 20 runs were made, which four cameras from different angles were recording. In total, 300 records of people boarding and overflows were analysed.

Additionally, Kraft and Deutschman [20] used an Erlang distribution simulations to analyse bus dwell time using data from photographic studies. The Erlang distribution is a special case of the Gamma distribution.

3. Methodology

In order to obtain the dwelling times, two bus companies which operate urban transit routes in different areas of the metropolitan area of San Jose, Costa Rica facilitated videos from the front door of the buses. In Costa Rica, the transit service is provided by contractors and regulated by the national government.

Tab. 1 Summary of consulted models in the literature regarding bus dwelling times

Author	Study Place	Proposed Model
Feder [6]	Pennsylvania	$DT = 1.31 + 2.573*BA$
Levinson [22]	United States	$DT = 5.0 + 2.75*BA$
Guenthner and Sinha [13]	Wisconsin	$DT/passengers = 5.0 – 1.2*\ln(BA)$
Guenthner and Hamat [12]	Michigan	$DT_B = -0.27 + 5.66*B$ $DT_A = 2.25 + 1.81*A$
York [33]	England	$DT = D + t_a*A + \sum(t_{bi}*B_i)$ (buses with a door) $DT = \max\{D + t_a*A + \sum(t_{bi}*B_i)\}$ (buses with two doors)
Gibson, Fernández and Albert [8]	Santiago, Chile	$DT = (D + D'\delta_1) + \max_j\{(t_b + t'_b\delta_1 + t''_b\delta_2)B_j + (t_a*e^{(-\beta*A)} + t''_a\delta_3)A_j$
Puong [28]	Boston	$DT = 12.22 + 2.27*B + 1.82*A + 6.2x10^{-4}*TS_d^3*B$
TCRP [30]	United States	$DT = A*t_a + B*t_b + t_{oc}$
Dueker, Kimpel and Strathman [4]	Portland	$DT = 5.136 +3.481*B – 0.04*B^2 + 1.701*A - 0.031*A^2 – 0.144*ONTIME + 1.364*TOD2$

D: dead time of boarding, alighting or both
D': dead time per stop
δ_1: if the platform is full, it is equal to 1
δ_2: if 4 or more passengers go up, it is equal to 1
δ_3: if bus hall is full, it is equal to 1
t'_b: boarding time per passenger
t'_a: alighting time per passenger
β: exponential function parameter
TS_d: number of passengers standing per door
t_{oc}: door opening and closing time

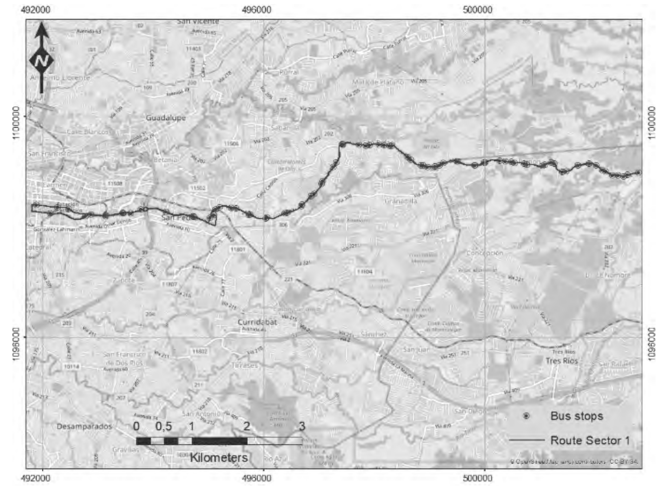

Fig. 1 - Detailed of the routes studied in Sector 1

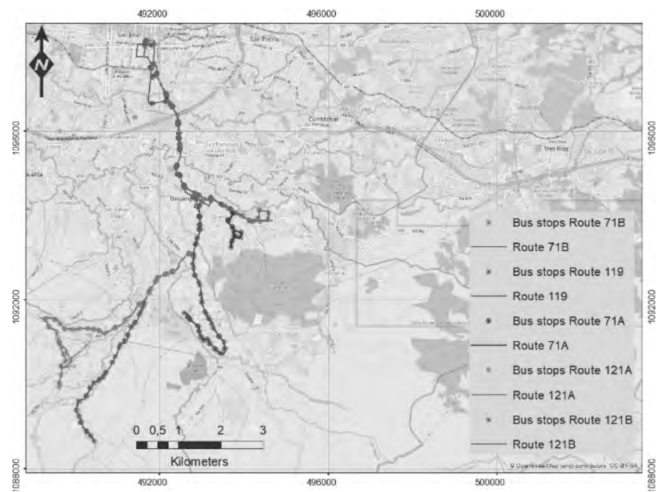

Fig. 2 - Detailed of the routes studied in Sector 2

The first sector analysed included the bus route 50 that goes from downtown San Jose to the east (see Figure 1) with a length of 13 km and 36 stops per trip. The second sector analysed comprised five different routes (routes 71A, 71B, 119, 121A, and 121B) in the south part of the city (see Figure 2); the routes´ lengths for this sector vary from 7 to 12.5 kilometers and the number of bus stops between 25 and 45 per trip.

The data were collected using the videos of the security cameras located at the front entrance of the buses to clearly observe when the bus doors are opened and closed. Figure 3 shows, as an example, the configuration of what is observed in the videos studied. Only videos from non-peak hours were considered to eliminate the effect of additional boarding times experienced by the users when the bus is crowded. Further details regarding the effects of bus crowded level are studied by Bie et al. [2].

Fig. 3 - Passenger boarding, screenshot of a security camera

An initial exploratory analysis of the collected information was performed, modelling the dwelling times using linear models. According to Isukapati et al. [17] linear regression models (LRM) require a transformation of the times, since ordinary linear regression models could not be adequate to analyse dwelling times. Additionally, Glick and Figliozzi [11] indicate the assumption of homoscedasticity is frequently violated when LRM are used in the analysis of dwell times.

Therefore, as a first step a logarithmic transformation was applied to the response variable. Glick and Figliozzi [10] present an analysis applying log-linear and quantile regression models to predict bus dwell times. Also, Kostyniuk and D'Souza [19] applied a natural logarithm of dwell time; however, form their residual analysis, they found that the model underestimates the dwell time for set of cases. Subsequently, the data were modelled following a Poisson distribution. Finally, the evaluation was performed using generalized linear models, since it represents an alternative transformation of the response variable for data that do not appropriately fit to normal distributions. Therefore, the gamma distribution was used for the data adjustment, taking into account that it is a suitable function to model random variables with positive asymmetry.

The gamma distribution has been proposed to model time data since it is positive and right-skewed. The gamma distribution is defined as follows:

$$Y \sim Gamma(\upsilon, \lambda) \quad with\ f_Y(y) = \frac{\lambda}{\Gamma(\nu)}(\lambda y)^{\nu-1}e^{-\lambda y} \qquad y \geq 0 \tag{1}$$

where Y is the observed data vector, υ is the shape parameter $(\upsilon > 0)$, λ is the rate parameter $(\lambda > 0)$, and $\Gamma(x)$ is the gamma function $\Gamma(x) = \int_0^\infty z^{x-1}\, e^{-z}dz$.

The gamma distribution has the following mean:

$$E(Y) = \frac{\upsilon}{\lambda} = \mu \tag{2}$$

and variance:

$$VAR(Y) = \frac{\upsilon}{\lambda^2} = \left(\frac{\upsilon}{\lambda}\right)^2 \frac{1}{\nu} = \mu^2 \frac{1}{\nu} \tag{3}$$

Then, the generalized linear model estimates are:

$$\mu_i = \frac{\nu}{\lambda_i} \qquad \sigma^2 = \frac{1}{\nu} \tag{4}$$

And with an identity link the expectation is:

$$\mu_i = E(Y_i) = \beta_o + \beta_1 x_{i1} + \ldots + \beta_p x_{ip} \tag{5}$$

where *p* is the number of covariates. The model was estimated using the glm function of R [29].

4. Limitations

The variable bus stop was not included due the lack of standards regarding their configurations in Costa Rica making very difficult its classification. Most of the videos provided only come from cameras recording towards the front door, therefore, in order collect data with an adequate circulation within the bus only off-peak periods were considered. Because very few observations of users with physical disabilities were collected they were not included in the analysis.

5. Data collected

The data were collected between September 2016 and June 2017, excluding the information from the months of December to March, since it is the school vacation period in Costa Rica; in order to eliminate a possible changes in user´s patterns. A total of 1217 dwelling times were obtained from six bus routes, during off peak periods. One of the evaluated routes was a low-floor bus while the remaining were five had high-floor units.

Tab. 2 - Descriptive statistics of each considered variable

Variable	Condition	n	Average Time (s)	Max Time (s)	Min Time (s)	Standard Deviation (s)
Complete payment	Yes	490	22.7	70.6	4.9	11.6
	No	727	23.6	90.1	4.2	13.3
ID	Yes	55	36.4	76.3	14.8	13.5
	No	1162	22.6	90.1	4.2	12.2
No payment	Yes	40	26.4	90.1	5.0	15.2
	No	1177	23.1	84.2	4.2	12.5
Low-Floor bus	Yes	345	20.3	70.7	4.2	11.6
	No	872	24.4	90.1	6.3	12.8
Bus sector	South	599	25.5	90.1	6.3	12.9
	East	618	21.0	79.5	4.2	11.9
Number of passengers boarding	0	442	16.5	42.0	4.2	6.5
	1	262	17.4	48.1	4.9	7.3
	2	139	22.3	49.7	9.8	7.7
	3	114	27.5	51.8	14.3	8.0
	4	85	29.0	51.2	18.7	7.6
	5	64	36.4	67.4	20.6	10.5
	6	33	41.3	79.5	31.7	10.5
	7	28	48.0	76.9	28.3	12.3
	8	25	48.3	70.6	32.1	10.4
	9	7	52.7	64.4	36.4	9.7
	10	13	59.7	90.1	43.4	14.8
	11	2	61.8	64.6	59.0	4.0
	12	1	76.6	76.6	76.6	-
	14	2	57.3	70.7	43.9	18.9
Number of passengers alighting	0	585	25.7	84.2	4.9	12.9
	1	325	17.5	76.9	4.2	10.3
	2	156	21.0	67.4	7.3	10.4
	3	69	23.0	51.2	9.8	9.2
	4	31	27.2	58.7	13.8	10.3
	5	16	26.3	57.4	14.5	9.6
	6	16	35.8	79.5	18.4	18.2
	7	6	34.9	42.4	25.2	7.4
	8	1	63.0	63.0	63.0	-
	9	3	32.7	44.7	19.4	12.7
	10	3	49.1	90.1	27.1	13.8
	11	1	29.9	29.9	29.9	-
	14	1	58.2	58.2	58.2	-
	16	1	49.8	49.8	49.8	-
	17	1	64.2	64.2	64.2	-
	19	1	48.1	48.1	48.1	-
	21	1	38.9	38.9	38.9	-

The variables considered for the analysis were taken from similar studies, such as those cited in Table 1. Below, each of the variables that were significant for the model is briefly described.

Dwelling Time: it is the time a bus spends at a bus stop without moving. It was recorded from the opening of gates to the total gates closing again.

Number of passengers boarding/alighting: number of people boarding/alighting the bus at the stop.

Exact fare: It occurs when the passenger pays the exact amount to the driver and no change is given in return.

ID: elderly users in Costa Rica have a payment exemption. To get the exemption they must show their ID to the bus driver as a proof of their age. Usually bus drivers have to register manually the ID number, or pass the ID through an ID scanner.

No payment: users who did not pay their fare when boarding the bus, and do so at any other time during the trip.

Low-Floor Bus: when the type of bus used is low floor

Bus Route: In the study, six bus routes from two different sectors of San Jose's city (south and east) were considered, which showed to be statistical different; therefore, an indicator for route was introduced to account for it.

Some limitations of this study include that only buses with similar door width were analyzed, the queue discipline´s considered is first arrived first served (also known as first in, first out), since is the typical . Only passengers in front door are considered due to lack of cameras in the rear door; however, some passengers alight using the rear door. Additionally, the layout of the bus stop was not considered.

Finally, the respective regressions were carried out involving all the data used throughout the study, which in total were 1 217 stops analyzed. The general average number of users per stop is two passengers, varying from 0 passengers boarding to 14. Additionally, on average 1.1 passengers alight per stop varying from 0 passengers alighting to 21. Only passengers using the front door were considered in this study. The width of the front door was similar for all buses included in this study.

6. Results

Initially, a linear regression model was applied. However, the residuals do not follow a normal distribution violating the assumption of homoscedasticity. The Box-Cox transformation was applied and the lambda value obtained indicates a logarithmic transformation of the boarding times. However, the log-linear model did not solve the issue related to heterodasticity, and the outliers could be similar to the ones founded by Kostyniuk and D'Souza [19]. Therefore, generalized linear models where applied to overcome the heterodascity.

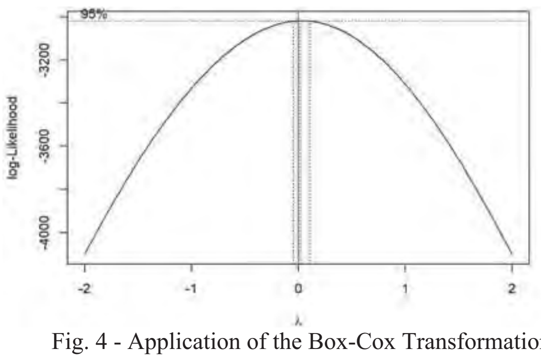

Fig. 4 - Application of the Box-Cox Transformation

Tab. 3 - Generalized linear model with a gamma and a Gaussian distribution results

	Gamma distribution				Gaussian distribution			
	Estimate	STD. Error	t Value	Pr(> ltl)	Estimate	STD. Error	t Value	Pr(> ltl)
Intercept	11.272	0.333	33.824	< 2e-16	12.394	0.409	30.291	< 2e-16
Boarding	4.723	0.108	43.54	< 2e-16	4.548	0.075	60.612	< 2e-16
Alighting	2.777	0.131	21.114	< 2e-16	2.201	0.096	22.94	< 2e-16
Exact fare	-0.815	0.322	-2.533	0.011	-0.56	0.383	-1.462	0.144
ID	7.905	1.133	6.978	4.96e-12	8.416	0.847	9.941	< 2e-16
No payment	-1.519	0.869	-1.478	0.081	-0.968	0.976	-0.991	0.321
Low-Floor bus	-4.824	0.346	-13.395	< 2e-16	-5.339	0.487	-10.961	< 2e-16
Bus sector	2.143	0.398	5.389	8.50e-08	1.713	0.459	3.734	0.0002
D^2	76 %				78 %			
Null deviance	319.04				193641			
Residual deviance	77.94				42728			
AIC	7476.3				7802.3			

The results obtained when analyzing the data by means of a generalized linear model with the gamma distribution are presented in Table 3 together with their respective parameters. The model was formulated evaluating only the passengers who boarded and alighted the bus through the front door and considering the stop time as the total duration of the maneuver, starting when the doors open until they are completely closed.

The null and residual deviances showed that the Gamma model is better than the Gaussian model. The AIC also shows that the Gamma model is significantly better than a traditional linear model with Gaussian error term. These results support the hypothesis of using a strictly positive distribution to model dwell times, given the nature of the response variable. In addition, the Gamma model presents lower standard errors of the coefficients in general, which implies more precise estimates.

According to the results of the Gamma model, the dwell time by stop increases 4.72 seconds for each person boarding. This is similar to the results obtained by [13, 27]; when compared to 3.48 seconds according to Dueker et al. [4] it is also consistent if the effect of the non-peak hour is considered, which adds 1.364 seconds. Regarding the number of passengers alighting similar estimates were obtained by [4,12,27,28].

Low-floor buses have significantly lower dwelling times. The reduction in dwelling times for low-floor buses is about 4.8 seconds by stop which easily adds up to several minutes in the course of single trip. Similar results were obtained by Mohammad et al. [27], who found a reduction of almost 4 seconds in the dwell time for low-floor buses.

Regarding the payment method, only one of the reviewed studies considers this variable as significant [8], and passengers who paid exact fare represent a decrease in the dwelling time. However, it is known that in other countries this operation is already programmed under a technological application, for example, by a prepaid card, which in Costa Rica has only been implemented in rail services. Differences between the buses operating on the south side and the east side of the city were found; however, not a clear reason was found for this difference.

Additionally, detailed models were generated for buses from Sector (zone) 1. The data of low buses and high flor were separately modeled. A separate model with all the data from Sector 1 (all buses) was also generated. In all cases, the statistic tests allow to reject the null hypothesis.

Tab. 4 - Likelihood test for different scenarios

Scenario	Model	d.f.	Residual Dev.	(p-q)	χ^2	P(>lChil)
High-Floor Sector 1	Reduced	272	68.313			
	Full	269	18.212	3	50.101	2.20e-16
Low-Floor Sector 1	Reduced	344	108.930			
	Full	340	21.430	4	87.502	2.2e-16
All Buses Sector 1	Reduced	617	177.98			
	Full	612	40.263	5	137.72	2.20e-16
All buses both sectors	Reduced	1205	305.121			
	Full	1200	77.349	5	227.77	2.20e-16

Tab. 5 - Generalized linear model with a gamma distribution results by floor configuration for buses in Sector 1

	High-Floor Sector 1		Low-Flor Sector 1		All buses Sector 1	
	Coef.	P value	Coef.	P value	Coef.	P value
Intercept	11.047	<2e-16	6.076	<-16	11.015	<2e-16
Boarding	5.242	2e-17	4.384	<2e-16	4.573	<2e-16
Alighting	2.451	1.16e-16	2.843	2.15e-15	2.673	<2e-16
Non-exact Fare	-	-	2.075	5.79e-08	1.496	0.003
ID	5.985	0.052	7.140	2.14e-17	6.801	4.61e-06
Low-Floor	-	-	-	-	-4.793	<2e-16
D^2	73 %		80 %		77 %	

The separate models for low-floor and high-floor buses, confirm the importance of bus floor height in the dwelling time. This difference could be noted in the intercept for these two models and also as the low-floor coefficient for the model generated for all buses in Sector 1.

7. Discussion and conclusions

The generalized linear model (GLM) analysis under a gamma regression, provides a more flexible alternative, in cases where the predictor variables are strictly positive. According to the results obtained, it is a better alternative to perform the analysis by means of a gamma regression, using generalized linear models, when working with time data, and covariables of categorical nature, as is the case of the present work. The application of generalized linear models using the gamma distribution allows to determine the factors that significantly affect dwell time.

According with the results obtained in urban transit routes in Costa Rica, during off peak periods, the dwelling time is determined by the following factors:

a) Number of people boarding the bus at each stop,
b) number of people alighting at each stop,
c) the payment method,
d) the type of bus floor, and
e) the bus route.

The bus route factor could consider the population type and other socio-geographical and operational conditions; however, additional research is required to determine why the bus route is an explicative factor. The results suggest that, in order to promote faster and more efficient transit systems, public policies should encourage the restriction of cash payments (or at least exact fare policies) within the bus. Initiatives like the Paid Zones systems implemented at bus stops in the City of Santiago, Chile where the payment is made in order to access the bus stop before boarding the bus could reduce dwelling times; therefore, improving the service’s reliability. Additionally, the validation method for elderly passengers should be updated.

Additionally policies that promote the use of low-floor buses by contractors could have an impact on accessibility and reduce travel times since low-floor buses could decrease approximately 5 seconds in each stop when they are compared with other buses. Assuming that an average of 40 stops per trip would mean a saving of 3 minutes and 20 seconds per trip, taking into account that the average travel time is 38.42 minutes, according to [3], it could be said that the use low floor buses, meaning savings of 11.5 % in travel times of public transport.

Future research is necessary to determine the effects of social distancing during epidemics. Future studies could explore other probability distributions with continuous and positive values skewed to the right. Additionally, other elements such as the circulation patterns inside the buses, the ratio of boarding to existing passengers, weather conditions, the bus stop location and the spacing of bus stops could be explored in future research. The use of automatic collection systems, such the ones used by [5,27] , could reduce significantly the data collection efforts. Also the applications of novel techniques such neural networks [1] or a Hierarchical Bayesian framework seem promising [16].

Finally, other variables, such as size and shape of corridors, location of payment/validation zone without impeding further passengers to board, among others could be explored in further research. Other factors that also affect bus travel time such intersection´s design and traffic light optimization and transit priority measures could be explored and analyzed.

8. Data availability statement

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

9. Appendix

Acronyms for variables

D: dead time of boarding, alighting or both
D': dead time per stop
δ_1: if the platform is full, it is equal to 1
δ_2: if 4 or more passengers go up, it is equal to 1
δ_3: if bus hall is full, it is equal to 1
t'_b: boarding time per passenger
t'_a: alighting time per passenger
β: exponential function parameter
TS_d: number of passengers standing per door
t_{oc}: door opening and closing time

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