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Research Article

Challenges for public transportation: Consequences and possible alternatives for the Covid-19 pandemic through strategic digital city application

Luis Andre Wernecke Fumagalli [a,b,*], Denis Alcides Rezende [a,c,d,e,f], Thiago André Guimarães [g,h,i,j]

[a] Pontifícia Universidade Católica do Paraná (PUCPR). R. Imaculada Conceição, 1155 - Prado Velho, 80215-901, Curitiba, PR, Brazil
[b] FAE Business School (FAE). Av. Visconde de Guarapuava, 3263 - Centro, 80010-100, Curitiba, PR, Brazil
[c] Strategic Digital City, 2013-2014, School of Public Service (DePaul University, Chicago-EUA), USA
[d] USP University, Brazil
[e] Information Technology and Public-Private Strategic Planning, UFSC University, Brazil
[f] Information Technology, UFPR University, Brazil
[g] Research Group of Technology Applied to Optimization (GTAO), Federal University of Paraná (UFPR). Av. Prefeito Lothário Meissner, 632, Jardim Botanico, Curitiba, Paraná, Brazil
[h] Department of General and Applied Administration (DAGA), UFPR University, Brazil
[i] Federal Institute of Education, Science and Technology of Paraná (IFPR). Visiting Researcher at the Center interuniversitaire de Recherche sur les Réseaux Entreprise, la logistique et le Transport (CIRRELT), Université Laval in Québec, Canada
[j] Operational Research by the Graduate Program in Numerical Methods in Engineering), Area of Concentration: Mathematical Programming, at UFPR, Brazil

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ABSTRACT

Public transport was already one of the biggest issues for all municipalities where people are highly concentrated at the same space at the same time. With COVID-19 pandemic and social distancing consequences, mass transportation is actually the main barrier for students and workers dependents of transport to go back to their daily routines with comfort and safety. Thus, the objective is to determine a demand control able to equalize the number of passengers in each car, respecting the COVID-19 social distancing protocols. The number of passengers in each time-of-day range were combined in four different models that included independent variables related to passenger's behavior indicating that almost 90% of all passengers are following a very strict and straight daily routine that can be coordinated and scheduled creating enough time space one from the other to avoid undesirable concentrations inside buses and bus stops. In conclusion, a very accurate urban management tool can arise from the study and may be able to solve not only the pandemic issues but also to improve local public services efficiency, to attract private investments and to improve citizen's quality of life.

1. Introduction

Public transport was already one of the biggest issues for all municipalities, especially in big metropolitan cities where people are

* Corresponding author. FAE Business School (FAE). Av. Visconde de Guarapuava, 3263 - Centro, 80010, Curitiba, Brazil.
E-mail addresses: luis.fumagalli@fae.edu (L.A.W. Fumagalli), denis.rezende@pucpr.br (D.A. Rezende), thiagoandre@ufpr.br (T.A. Guimarães).

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highly concentrated at the same space at the same time. Now, with COVID-19 pandemic and social distancing consequences, mass transportation is actually the main barrier for students and workers dependents of transport to go back to their daily routines with comfort and safety. On the other hand, municipalities and transport operators are facing many challenges to organize all passenger fluxes to serve all needs and new regulations without losing efficiency and profitability with adequate and acceptable prices for users.

The current research is being made in Curitiba (Brazil) where public transport is made exclusively by private bus operators controlled by the city administration that is responsible to ensure quality, calculate and determine fee values and also to subside citizens that cannot afford it and/or have gratuity granted by law. The system was already facing many issues to equalize all involved costs with a big number of users overcrowding buses in the rush hours before the pandemic and now the challenge is much bigger not only in terms of infrastructure, system efficiency and investments. In order to reach satisfaction to all involved parts, there is a need to reorganize daily routines and schedules to move people from their points of origin to their destinations in a real time demand coordination to avoid crowding and time and money losses.

Therefore, this study seeks to answer the following research problems: (i) to observe and to find any patterns in passengers' daily behavior; (ii) and what are the main variables responsible for passenger's decision to take public transportation or other modal. From these preliminary results, the research question arises: is it possible to determine the demand for public transport to organize it so as not to create agglomerations in times of pandemic?

Thus, the objective is to determine a demand control able to equalize the number of passengers in each car, respecting the COVID-19 social distancing protocols. Many passengers are switching from public transport to private cars causing instability in demand and increasing traffic congestion, pollution and time loss (Bass et al., 2011). Crowding in public transport systems also have implications for the estimation of demand (Tirachini et al., 2013). Rider characteristics must also be considered and included in the model in order to include coordinated supportive policies able to attract passengers to public transport (Buehler & Pucher, 2012; Daldoul et al., 2016).

Daily information was collected from express bus line 503 responsible for about 6% of the entire city's public transportation from January 07, 2019 up to February 20, 2020. In terms of research methodology, the number of passengers in each day range time were combined in four different models that included independent variables like day class, weather conditions, bus capacity and other binary general variables like school day, pay day and crime indicating that almost 90% of all passengers are following a very strict and straight daily routine, mostly, from their houses up to school and work and back, that can be coordinated and scheduled creating enough time space one from the other to avoid undesirable concentrations inside buses and bus stops due to COVID-19 pandemic.

This study is justified since demand control is a strategic need for all cities and must be used not only to improve public transportation but also to combine it with other public services like the educational and health systems and other places of work, study, leisure and all other citizen's activities. Travel demand estimation is the most essential tasks for transport planners (Pulugurta et al., 2014) and how accurate or inaccurate this estimation can be (Flyvbjerg et al., 2007) still being a problem to all municipalities.

Due to this fact, a strategic digital city (SDC) project (Rezende, 2012) is adequate to be applied since the study objective is not only to create a management tool capable to predict demand but also to organize passenger trips, scheduling it according to their daily appointments in order to have buses capacity in an optimal usage level for users and operators. This study can contribute to a sustainable public transport system (Ryley et al., 2014), respecting not only the number of persons allowed per car but also taking in consideration other important indicators like fee and gas prices, weather conditions and other alternative transport offers.

This article is structured following the research process. Section 2 presents the theoretical review that supports research, with a special focus on the central concepts studied (public transport, pandemic and strategic digital city) in order to determine which variables can be used in order to determine passenger's behavior. Methodology is described in Section 3. There is presented where the phenomenon is observed and how the selected variables that may affect passenger's decision to take public transportation or not were tested. All used methods are presented in this section as well. At Section 4, results are presented and discussed, and the earned results derived from that are shown at Section 5. At the end of the article, in Section 6, conclusions are made with proposals for implementation in the city administration, and limitations and suggestions for further research are also made.

2. Literature review

2.1. Public transportation and pandemic

Public services should aim to maximize citizens utility that is difficult to achieve due to the own nature of public transportation, which offers a homogeneous service for all users without taking in consideration any individual preferences contributing to create disparities (Andreassen, 1995). Managing public transport is very difficult but the lack of it is even worse, which can be translated into issues in accessing life in society, education, health and economic opportunities, especially among the poorest (Willoughby, 2020).

The passenger's decision about which type of transport will be used is a complex task and it is often based on endogenous preferences (ethical and aesthetic) that are very difficult to predict and have no uniformity and consistency. On the other hand, all transportation systems are designed according to rational technical analysis and engineering solutions creating a gap in terms of satisfaction for all involved stakeholders: passengers, operators and municipalities. All these groups have conflicting interests since comfort, profit and efficiency are not normally equalized in terms of transportation planning and operation.

User satisfaction studies are very important to understand the main points of improvement in the service provided. It is essential that the model of analysis is in accordance with the situation, including issues with sample limitations and research methods. Chica-Olmo et al. (2018) concluded that public transport users don't perceive service quality levels in the same way. Therefore, an indispensable factor for a good satisfaction analysis is the heterogeneity of users in the model (Echaniz et al., 2018). In more basic and punctual situations, simpler equation models can be used to determine user satisfaction. For this case, Eboli and Mazzulla (2007) proposed a structural equation model to show the relationship between passenger satisfaction in public transport and the provided service attributes.

Satisfaction cannot be measured in objective terms, but in the abstract, as a weighted average of multiple indicators (Andreassen, 1995). Service quality is multidimensional, where technical and functional factors have considerable importance (Chica-Olmo et al., 2018). Ranking the quality attributes of public transport is part of the process of improving satisfaction. Knowing this, Guirao et al. (2016) developed a method to estimate the importance of each quality criterion in public transport. Using direct user preference surveys, the proposed hierarchy model has the advantage of a reliable estimate of satisfaction even with a smaller sample of users.

Agrawal et al. (2015) developed a study that sought to measure public transport service quality in Delhi, India. To decrease the subjectivity problem in the questionnaire's answers, the researchers used more complex decision-making methodologies to help in choosing the best criteria, by ranking them. The analysis revealed that numerous problems related to traffic congestion, pollution, among others, can be reduced by increasing the quality of public transport service. In addition, the method of the article helps public transport operators to improve their decision making by comparing their performance with other companies in terms of quality. To maintain quality in public transport, Rojo et al. (2015) have proposed the amendment of public transport operations contracts, including requirements for maintaining the provided service quality. Research results showed that, without any increase in the operation cost, the necessary subsidy due to the service underutilization can be reduced by increasing demand through the provision of a more attractive public transport service.

In order to understand quality aspects of public transport that can best attract car users, Redman et al. (2013) developed a study that mainly sought to answer two questions: (i) which quality attributes of public transport are attractive for users?; (ii) what changes in the quality attributes of public transport services are capable to encourage modal transition from private to collective? It is concluded that, although criteria such as reliability and frequency of service are important in public transport, those capable of attracting car users are more connected to individual perceptions. Reducing fares and changing policies are more effective in encouraging car users to switch to public transport. Other attributes such as accessibility, reliability and mobility provision, perceived by the market as important quality services, must be provided to maintain the user after changing the modal.

This modal's change requires a greater understanding from planners and public transport operators about the difference between desired quality and quality perceived by users. Knowing this, the study made by Dell'Olio et al. (2011) concluded, using focus groups and decision-making models' variables calibration, that the most important variables presented by bus users were different from those presented by potential users. Among public transport users, the three attributes that appear most relevant were: waiting time, cleanliness and comfort.

For Tirachini et al. (2014) the main element in transport research is the time savings monetization promoted by investments in infrastructure and management to reduce travel time. However, the authors point out that users not only want fast, but also reliable transport. Arrival time uncertainty affects the modal's choice and variability in route and departure time affects transport costs reflected on fare prices.

In a research on public transport operation optimization, Ceylan and Ozcan (2018) proposed a two-level model to perform simulations capable to find benefits possibilities for passengers and bus operators. Hafezi and Ismail (2011) developed a study on different models of bus schedules, where they included real data in their equations in many possible scenarios, reaching reductions in bus capacity greater than 60%. In addition to the travel time and bus capacity, Misiurski (2015) concluded that buses technical parameters are also important factors that can negatively affect several main decision-making attributes.

For this reason, many models have been built and studied over the years. According to Flyvbjerg et al. (2007) at least half transportation projects are misleading traffic forecasts in more than ± 20%. Zhao & Kockelman (2001) also investigated the stability of transport model demand outputs by quantifying the variability in model inputs suggesting that uncertainty is likely to compound itself over a series of models.

In addition to all those difficulties regarding variables and models, COVID-19 pandemic brought a new and critical situation that must be taken in consideration not only by passengers, but also to operators and municipalities. There is a maximum number of passengers allowed per car that cannot be surpassed without putting people in risk of contamination. Human infection risks could be extremely high when considering the exposure time, transmission routes and structural characteristics during travel or work, resulting in the rapid spread of infections (Shen et al., 2020). Chen et al. (2020) have studied different close contact methods and cases and have found that the infection rate is highest when living with the case (13.26%), followed by taking the same means of transportation (11.91%).

Individuals need to explore the possibilities of changing their travel behavior in order to reduce their exposure to the disease, reducing traffic congestion and enhancing their wellbeing (Mogaji, 2020). Activity-based travel information has also been used as an analysis tool in the pandemic (Hendrickson & Rilett, 2020). Advanced activity-based models used in transportation and in epidemiology modeling are very similar, mainly because both are interested in predicting demand on a system based on detailed models of human interactions across space and time (Del Valle, 2020).

2.2. Strategic digital city

Unlike the conventional digital city and smart city concepts, the strategic digital city (SDC), a concept coined by Rezende (2012), can be understood as the information technology resources application in the city's management and also in the information and services provision to citizens, based on the city management strategies. It is a more extensive project than just offering internet to citizens through conventional telecommunication resources. It goes beyond digitally include citizens in the global computer network (Rezende, 2012). It is based on the city's strategies to meet different municipal thematic areas objectives (Rezende, 2018). It is divided into four subprojects: city strategies (to achieve the city's objectives); cities information (to assist in the citizens and city managers decisions); public services (to increase the citizens life quality); and information technology resources application (Rezende, 2018). It can also be understood as a public policy in cities (Rezende et al., 2015).

City strategies are ways or means to achieve city objectives (Rezende, 2018). Urban digital strategies can be understood as unconventional strategies in cities. There are parallel studies of smart city research since the 1980s (Bloomberg et al., 2010; Rezende, 2016) articulating digital opportunities in cities involving society and citizens, to make easier the smart city strategies implementation and ensure that the digital economy is a priority with integrated planning of cities (Alizadeh, 2017). City information can be understood as something useful for decision making processes by public managers and citizens and public services with information technology are transitional resources that allow interaction between governments and citizens (Rezende, 2018). Information technology (IT) can be understood as a set of computational resources for manipulating data and generating information for public managers and citizens, including hardware, software, telecommunications systems and data management (Rezende, 2018).

Based on city strategies, SDC is defined as the application of information technology resources in the management of the municipality and also in providing information and public services to citizens and city inhabitants (Rezende, 2012), as well as, cities can be divided into municipal themes, such as health, transport, education, security, agriculture, science and technology, sports, housing, industry, leisure, environment, sanitation, social, tourism, urban, rural, among others (Rezende, 2018).

3. Research methodology

In order to reach the research objectives, Curitiba – PR (Brazil) was chosen as a case of study and qualitative and quantitative methods were applied. Curitiba, capital of Parana State, has a territorial area of 434.892 km^2 with an estimated 1,933,105 inhabitant's population. It is in the country Southern Region. Local governance is structured in 12 Secretariats and 15 Public Agencies (IBGE, 2019; PMC, 2020). Summoned 1143 cases of *Covid-19* in the city until June, of which 53 deaths. Mortality per 100,000 inhabitants corresponds to 2.7 (IBGE, 2020). A map with Curitiba's location can be observed on Fig. 1.

Daily data from express line 503 (Boqueirão) were collected, regarding the number of buses operating on this line, the number of passengers boarded in each stop and the class of the day (weekdays, Saturdays, Sundays and holidays) in the period between January 07, 2019 and February 20, 2020. All information was extracted from Urbanização de Curitiba S/A (URBS) system, that collects and stores information, in real time, from all bus lines operating in the city. URBS is a public company subordinated to Curitiba's mayor's office responsible to manage and to supervise all city's public transportation system.

In addition to the numbers mentioned above, other variables observed and pointed out in the theoretical framework related to user satisfaction were collected and tested in four different mathematical models detailed in section 3.1. To explain the demand for passengers, eight independent variables were tabulated as follow:

- (X_{WD}): number of passengers boarded at express line 503 on working days (WD).
- (X_{SAT}): number of passengers boarded at express line 503 on Saturdays (SAT).
- (X_{SUN}): number of passengers boarded at express line 503 on Sundays (SUN).
- (X_{RAIN}): daily precipitation average in Curitiba, measured in millimeters (RAIN).

Fig. 1. Curitiba's location in Brazil/South America map.
Source: ToursMaps.com (2020).

- (X_{TEMP}): daily temperature average in Curitiba, measured in degrees Celsius (TEMP).
- (X_{LET}): school days defined in calendar in the observation period (LET).
- (X_{SAL}): period where wages are paid, which occurs between the 5th and 15th of each month (SAL).
- (X_{OC}): recorded occurrence of theft at some point in the path that the line takes in the observation period (OC).

The study was based in four lineal multiple regression models in order to measure which factors may affect the passenger's demand in the line. A hierarchical regression method was applied through sequential variable inclusion in each tested model. All testes generated a correlation matrix from where only the valid models were kept (Model 3 was excluded). Through the adjusted R square, it was possible to observe that the inclusion of the variables increases the degree of explanation of the model, starting from 0.847 to reaching 0.877, and the explanation is significant (F test).

An adjusted R square greater than 0.8 is quite satisfactory. Three hypotheses have been tested regarding the three remaining models and the best model to explain demand in the line were selected. After this, a variance analysis was used to test all 3 remaining models through ANOVA. The Statistical Package for Social Sciences (SPSS) version 22 was used to conduct the analysis.

3.1. Collected data arrangement and statistic models construction

The 503 express line operates daily from 5:00 a.m. until midnight (0:00 a.m.) and the number of buses on the line varies according to the class of the day. In addition to the class of the day, the fleet varies according to the different periods of the day, defined by URBS (Table 1). The number of buses on the line is always higher on weekdays and at peak times, which reduces the waiting time between buses. It is necessary to consider that the stopping time at stations increases significantly during peak hours, as there is a greater number of passengers embarking and disembarking.

This line connects the neighborhoods in the southern region of Curitiba city and the municipality of São José dos Pinhais, a city in the metropolitan region. The line has a total length of 10.3 km with a total of 19 stops distributed, on average, every 0.5 km along the route and is responsible for approximately 3.98% of the total number of passengers transported per day across the city.

The total daily demand (Y_{TOT}) is obtained by the direct sum of the number of passengers registered in each time range, being defined:

$$\boldsymbol{Y_{TOT}} = \boldsymbol{Y_{P1}} + \boldsymbol{Y_{M}} + \boldsymbol{Y_{P2}} + \boldsymbol{Y_{T}} + \boldsymbol{Y_{P3}} + \boldsymbol{Y_{N1}} + \boldsymbol{Y_{N2}} \tag{1}$$

To explain the demand for passengers, eight independent variables were tabulated in four groups, as follow:

Group 1: Day Class.

Variations were observed in the number of passengers depending on the nature of the day. Therefore, three binary variables were considered to capture this effect: the first referring to working days (X_{WD}); the second to Saturdays (X_{SAT}); and the third to Sundays and holidays (X_{SUN}).

Group 2: Climatic Factors.

The occurrence of rain was measured by the precipitation recorded in the day, in millimeters, measured by the variable (X_{RAIN})[fx]. The day's average temperature was also recorded, in degrees Celsius, represented by the variable (X_{TEMP}).

Group 3: Capacity.

The transport capacity (X^j_{CAP}) measures the average number of buses circulating in each class of day j (working days, Saturdays, Sundays and holidays). As the number of buses circulating varies along the time ranges, mainly due to peak times, but it is fixed for the same range in different day classes. Thus, the transport capacity was calculated from the observed data, being:

- N^j_i : Number of buses scheduled for time slot i in day class j, where $i = 1$ refers to P1, $i = 2$ refers to P2, and so on, e $j = 1$ refers to working days, $j = 2$ on Saturdays and $j = 3$ on Sundays and holidays.
- H_i : duration time in hours of range i.

Transport capacity is then calculated:

$$X^j_{CAP} = \frac{\sum_{i=1}^{6} \left(N^j_i * H_i\right)}{\sum_{i=1}^{6} H_i} \tag{2}$$

Group 4: General Binary Variables.

Due to the line structure, a binary variable (X_{LET}) takes the value one, when the day of the historical series is academic (according to the school calendar), and zero otherwise. There is also an additional binary variable (X_{SAL}) if the day of the historical series is under the influence of the period where wages are paid, which occurs between the 5th and 15th of each month. Finally, a third binary variable

Table 1
Time ranges defined for each day period.

Range	P1 (Y_{P1})	M (Y_M)	P2 (Y_{P2})	T (Y_T)	P3 (Y_{P3})	N1 (Y_{N1})	N2 (Y_{N2})
Start	05:00	08:30	11:30	14:00	17:30	19:30	22:00
End	08:30	11:30	14:00	17:30	19:30	22:00	23:59

(X_{OC}) takes the value one if there is a recorded occurrence of theft at some point in the path that the line takes, and zero otherwise.

3.2. Regression models

The following multiple linear regression models were operated using SPSS software:

Model 1.

The objective of Model 1 is to verify the structural factors in determining the demand for passengers on the line, considering only the binary variables of Group 1. In this case, the following regression was performed:

$$M1:\ Y_{TOT} = \beta_0 + \beta_1 X_{WD} + \beta_2 X_{SAT} + \beta_3 X_{SUN} \tag{3}$$

Model 2.

Model 2 aggregates the climatic variables from Group 2 to Model 1, resulting in

$$M2:\ Y_{TOT} = \beta_0 + \beta_1 X_{WD} + \beta_2 X_{SAT} + \beta_3 X_{SUN} + \beta_3 X_{RAIN} + \beta_4 X_{TEMP} \tag{4}$$

Model 3.

Model 3 adds the capacity independent variable to Model 2, resulting in

$$M3:\ Y_{TOT} = \beta_0 + \beta_1 X_{WD} + \beta_2 X_{SAT} + \beta_3 X_{SUN} + \beta_3 X_{RAIN} + \beta_4 X_{TEMP} + \beta_5 X_{CAP} \tag{5}$$

Model 4.

Model 4 includes the variables of the corresponding group, resulting in

$$M4:\ Y_{TOT} = \beta_0 + \beta_1 X_{WD} + \beta_2 X_{SAT} + \beta_3 X_{SUN} + \beta_3 X_{RAIN} + \beta_4 X_{TEMP} + \beta_5 X_{CAP} + \beta_6 X_{LET} + \beta_7 X_{SAL} + \beta_8 X_{OC} \tag{6}$$

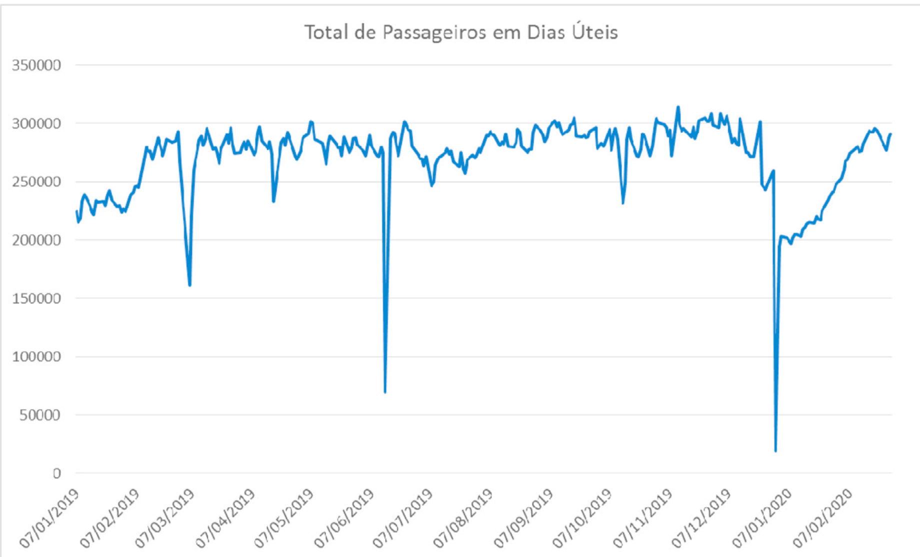
4. Research results and discussion

4.1. Preliminary graphical analyses

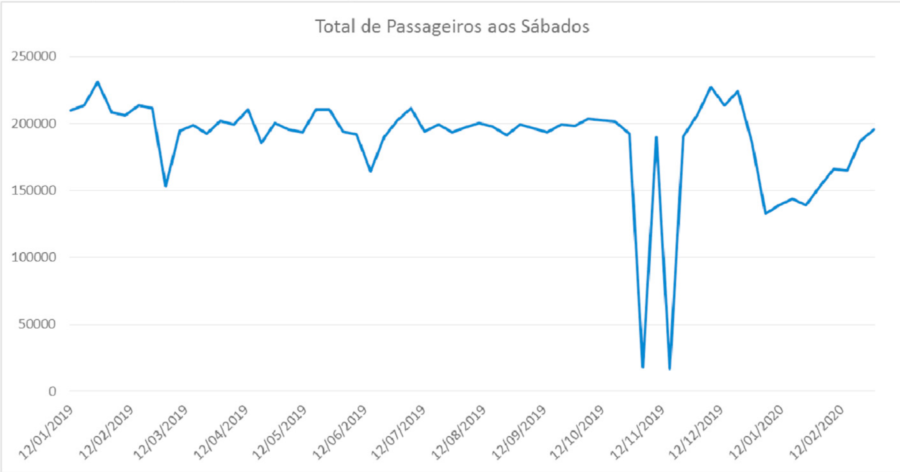
Graph 1 shows the number of passengers for the entire period of the database on working days. It is possible to observe that there are no great variations for the academic period, this factor being the main determinant of demand. At the same time, demand decreases during school vacation periods. There are also sharp drops in demand on the occasion of extended holidays, such as the 2019 carnival.

The number of passengers on Saturdays shows little variation, being affected occasionally by two long holidays in 2019 (11/2) and (11/15), in addition to a structural decline at the end of the school term as per shown in Graph 2.

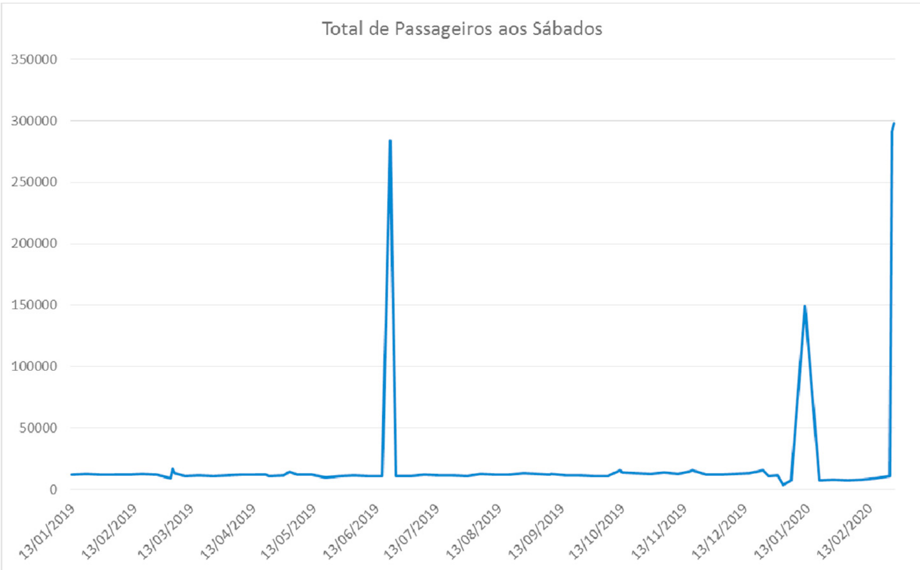
Finally, Graph 3 shows the demand for Sundays and holidays. There is an effect of complementarity with the class of working days. The demand on Sundays is higher precisely during periods of school holidays, with a peak registered at the carnival of 2020.



Graph 1. Total passengers on working days.



Graph 2. Total passengers on Saturdays.



Graph 3. Total passengers on Sundays/Holidays.

Table 2
Descriptive statistics.

	Mean	Std. Deviation	N
Total_Pass	217916,71	99495,433	419
Weekday	,69	,462	419
Sat	,14	,346	419
Sun_Hol	,17	,376	419
Rain	3376	9,6396	419
Temp	19,063	3,7991	419
Cap	6190	,6368	419
School	,53	,500	419
Ocurr	,09	,288	419
Pay_Day	,36	,481	419

4.2. Statistical analyses

Multiple linear regression was operated with all four models using the hierarchical regression method, where the variables hosted in each tested model were sequentially inserted. Table 2 presents the descriptive statistics of the database. The average, standard deviation and number of observations for each variable are reported. It's noticeable that 69% of the observations are on working days, 14% on Saturdays and 17% on Sundays and holidays.

Table 3 shows the correlation matrix between all the considered variables, measured by Pearson's coefficient. In bold, strong correlations stand out (values in module greater than 0.7). It is possible to observe that the variables (X_{WD}), (X_{CAP})and (X_{LET}) are strongly correlated. This result was expected, since the school period coincides with working days, as well as the programmed fleet is expanded during peak periods, just when there is a greater flow of student passengers on the line. Due to the strong correlation, the variable (X_{CAP}) (Model 3) was excluded, and the hierarchical models considered became Model 1, Model 2 and Model 4.

Table 4 presents the models summary. As there the Model 3 was excluded, given the strong correlation between the variable (X_{CAP}) and (X_{WD}), the summary considers only the valid models. Through the adjusted R square column, it is possible to observe that the inclusion of the variables increases the model's explanation degree, starting from 0.847 to reaching 0.877, and the explanation is significant (sig F test).

The following hypotheses have been tested:

First Hypothesis.

H0. Model 1 adjustment = model adjustment without predictor

H1. Model 1 adjustment ≠ model adjustment without predictor

Conclusion: as the significance F test is lower than 0.05, the null hypothesis is rejected since the Model 1 adjustment is equal to model adjustment without predictor, that means that the structural variables of day classes are influencing the number of passengers in the line.

Second Hypothesis.

H0. Model 2 adjustment = Model 1 adjustment

H1. Model 2 adjustment ≠ Model 1 adjustment

Conclusion: as the significance F test is lower than 0.05, the null hypothesis is rejected since Model 2 adjustment is equal to Model 1 adjustment, that means that temperature and rain variables are contributing to variance explanation in the number of passengers. Thus, there is influence of climate variables in passengers' demand.

Third Hypothesis.

H0. Model 4 adjustment = Model 2 adjustment

H1. Model 4 adjustment ≠ Model 2 adjustment

Conclusion: as the significance F test is lower than 0.05, the null hypothesis is rejected since Model 4 adjustment is equal to Model 2 adjustment, that means that the additional binary variables are contributing to explain the number of passengers' variance. Thus, there is an influence on the academic period, the occurrence of thefts and crime and the pay day period influencing the number of passengers using the line. At the same time, the Durbin Watson test shows that the residuals can be considered independent, given the obtained value of 1.531 is in the range between 1.5 and 2.5. Finally, it is possible to conclude that Model 4 is the one that best explains the passenger demand for Line 503.

Table 4 presents the variance analysis for the three tested models. In this table, the comparison is made by testing the null hypothesis that the model (1, 2 or 4) individually is equal to a model without a predictor, against the alternative hypothesis that the model individually is different from a model without a predictor. Basically, the first hypothesis of the previous section is tested for the three considered models.

First Hypothesis.

H0. Model 1 adjustment = model adjustment without predictor

H1. Model 1 adjustment ≠ model adjustment without predictor

Table 3
Correlation matrix.

	(Y_{TOT})	(X_{WD})	(X_{SAT})	(X_{SUN})	(X_{RAIN})	(X_{TEMP})	(X_{CAP})	(X_{LET})	(X_{OC})	(X_{SAL})
(Y_{TOT})	1.000									
(X_{WD})	804	1.000								
(X_{SAT})	-.124	-.601	1.000							
(X_{SUN})	-.875	-.677	-.181	1.000						
(X_{RAIN})	.083	.067 -.013 -.070 1.000								
(X_{TEMP})	-.142	-.064	.033	.048	.011	1.000				
(X_{CAP})	.893	**.966**	-.372	-.845	.073	-.063	1.000			
(X_{LET})	.689	**.708**	-.426	-.479	.065	-.258	.684	1.000		
(X_{OC})	040	.031	-.006	-.032	.013	.003	.033	-.002	1.000	
(X_{SAL})	-.001	.030	-.029	-.010	-.065	-.040	.025	.044	.004	1.000

Table 4
Model's summary.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,921[a]	,848	,847	38919,237	,848	1157,916	2	416	,000	
2	,925[b]	,856	,854	37976,289	,008	11,457	2	414	,000	
4	,938[c]	,879	,877	34882,027	,023	26,569	3	411	,000	1531

a. Predictors: (Constant), Sun_Hol, Sat.
b. Predictors: (Constant), Sun_Hol, Sat, Temp, Rain.
c. Predictors: (Constant), Sun_Hol, Sat, Temp, Rain, Occurr, Pay_Day, School_Day.
d. Dependent Variable: Total_Pass.

Conclusion: as the significance F test is lower than 0.05, the null hypothesis is rejected since the Model 1 adjustment is equal to the model without a predictor, that means that the structural variables of the day classes are influencing the number of passengers of the line.

Second Hypothesis.

H0. Model 2 adjustment = model adjustment without predictor

H1. Model 2 adjustment ≠ model adjustment without predictor

Conclusion: as the significance F test is lower than 0.05, the null hypothesis is rejected since the Model 2 adjustment is equal to the model without a predictor, that means, the day class variables together with the climate variables are influencing the number of passengers on the line.

Third Hypothesis.

H0. Model 4 adjustment = model adjustment without predictor

H1. Model 4 adjustment ≠ model adjustment without predictor

Conclusion: as the significance F test is lower than 0.05, the null hypothesis is rejected since the Model 4 adjustment is equal to the model without a predictor, that means that the day class variables together with the climate variables and auxiliary binary variables are influencing the number of passengers on the line.

Table 5 shows that Model 1 excluded the variable (X_{WD}) due to its strong correlation with the variable (X_{CAP}). Thus, the parameters are:

$$M1: \ Y_{TOT} = 271196,79 - 84102,46X_{SAT} - 245724,07X_{SUN}$$

Coefficients are significant with 95% confidence, considering that the t-Student test for the dependent variables was less than 0.05 (sig column). As all values in the tolerance column are greater than 0.1, the model does not show collinearity between the dependent variables. This result is corroborated by the VIF column showing no value greater than 10. The model is, therefore, consistent.

Table 6 shows models' coefficients with their respective significance levels (Sig column next to column t), together with the collinearity tests.

Values interpretation shows that when $(X_{SAT}) = 0$ and $(X_{SUN}) = 0$, there is a working day. In percentage terms, Saturday reduces the number of passengers by approximately 31%, while Sundays and holidays reduce by approximately 90.6%. The standardized beta coefficient shows that the variable (X_{SUN}) is relatively stronger in explaining the dependent variable than (X_{SAT}) (0.928 versus 0.292).

Model 2 adds the climatic variables of rain and temperature. However, as the *t*-test for the rain variable was 0.426, it is not possible to guarantee that its coefficient is different from zero in the model, although there are no collinearity problems, as seen in the tolerance and

Table 5
Variance analysis (ANOVA).

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3507806500054,33	2	1753903250027,168	1157,916	,000[b]
	Residual	630118110409,297	416	1514706996,176		
	Total	4137924610463,63	418			
2	Regression	3540854434989,29	4	885213608747,324	613,795	,000[c]
	Residual	597070175474,338	414	1442198491,484		
	Total	4137924610463,63	418			
4	Regression	3637837978446,78	7	519691139778,112	427,112	,000[d]
	Residual	500086632016,851	411	1216755795,661		
	Total	4137924610463,63	418			

[a]. Dependent Variable: Total_Pass.
[b] Predictors: (Constant), Sun_Hol, Sat.
[c] Predictors: (Constant), Sun_Hol, Sat, Temp, Rain.
[d] Predictors: (Constant), Sun_Hol, Sat, Temp, Rain, Occurr, Pay_Day, School_Day.

Table 6
Model coefficients.

Model		Unstandardized Coefficients		STD Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	271196,790	2285,416		118,664	,000		
	Sat	−84102,462	5598,104	-,292	−15,023	,000	,967	1034
	Sun_Hol	−245724,071	5153,351	-,928	−47,682	,000	,967	1034
2	(Constant)	314435,385	9543,817		32,947	,000		
	Sat	−82881,786	5469,425	-,288	−15,154	,000	,965	1037
	Sun_Hol	−244121,296	5050,170	-,922	−48,339	,000	,959	1043
	Rain	153,991	193,261	,015	,797	**,426**	,994	1006
	Temp	−2318,548	489,992	-,089	−4732	,000	,996	1004
4	(Constant)	258564,697	11079,117		23,338	,000		
	Sat	−49400,904	6309,286	-,172	−7830	,000	,612	1635
	Sun_Hol	−210622,550	5998,535	-,795	−35,112	,000	,573	1744
	Rain	86,726	178,011	,008	,487	**,626**	,989	1012
	Temp	−1085,282	472,327	-,041	−2298	,022	,904	1106
	School_Day	44812,452	5077,762	,225	8825	,000	,452	2212
	Occurr	4767,109	5941,455	,014	,802	**,423**	,998	1002
	Pay_Day	−5233,956	3557,783	-,025	−1471	**,142**	,992	1008

[a]. Dependent Variable: Total_Pass.

VIF columns. The other dependent variables are significant. The numerical model result is given by the following equation:

$$M2: \; Y_{TOT} = 314435,4 - 82881,8X_{SAT} - 244121,3X_{SUN} + 154,0X_{RAIN} - 2618,6X_{TEMP}$$

In addition to the day class analyzes, it is interesting to note that the increase of 1 °C in temperature reduces the number of daily passengers by approximately 2618, and this value is significant. The rain variable coefficient is highlighted because it is not significant.

Finally, Model 4 is analyzed, which carries the greatest degree of explanation. Of the three binary variables added in relation to Model 2, two of them are not significant (period under the salary payment influence and theft/crime). The variable (X_{RAIN}) also remains non-significant. The tests did not detect the presence of multicollinearity between the independent variables (see tolerance and VIF columns). The numerical model is given by:

$$M4: \; Y_{TOT} = 258564,7 - 49400,9X_{SAT} - 210622,6X_{SUN} + 86,7X_{RAIN} - 1085,3X_{TEMP} + 44812,4X_{LET} + 4767,1X_{SAL} - 5233,9X_{OC}$$

For the described model, it is important to highlight that when the variable $(X_{LET}) = 1$, that is, when the school day is in effect, there is also the occurrence of a working day, that is, $(X_{SAT}) = 0$ and also $(X_{SUB}) = 0$. The analysis ceteris paribus, shows that on school days, there is an increase of approximately 18% passengers on the line. This value allows to infer that this is the share of students using the 503 line. The inclusion of these variables reduces the effect of temperature on the number of passengers, when compared to Model 2. There is also a softening of the effects of Sunday and Saturday. In this model, Saturday generates a passenger reduction of approx. 19% and 81,4% on Sunday.

5. Findings results & contributions

Analyzing the graphs and results in section 4 regarding the number of boarded passengers on weekdays, Saturdays, Sundays and holidays, it was possible to verify that they are quite stable, with variations lower than 10%, with greater variations only during the school vacation period. This stability is due to the fact that passengers are using public transport only to attend fixed appointments such as work and school. As entry times at companies and educational institutions follow a fixed schedule, it is also possible to deduce that the same people always take the same bus at the same time, every day, with few variations. It was possible to confirm this observation *in loco*, taking the same bus, at the same time, on different days. It was found that most people know which other from the bus, including the driver and the collectors at the boarding points.

Taking all mathematical equations is also possible to deduct that people still using public transportation only for two reasons: (i) it is cheaper in comparison to other transport options and/or free; (ii) and/or because there are no other options for certain users. In this direction, the study also reveals and confirms that the number of passengers that have to pay for transport is decreasing year by year with the gratuity arising in the other hand. This change on population's behavior is causing financial problems to operators to keep the system running and to the municipality is being forced to compensate it with public funds, not only to ensure public transport services but also to keep it comfortable, safe and attractive.

In this way, the demand forecasting model developed here can serve not only to define the number of cars needed on the line in each time range, with the optimum utilization of the bus occupation in a profitable way for operators, efficient for the municipality and for the public purse and with comfort and safety for users. It will be possible to avoid overcrowding on buses and stops with real time synchronization (which could be via mobile app) of the time and point of departure of each passenger according to the time and point of disembarkation of their destination. This project is typical of the strategic digital city, since the Municipality will be able to adjust the demand by integrating the transport needs of citizens, which may include other public services besides schools (such as health services, issuing documents, etc.) and other activities besides work, such as shopping and entertainment offered by private companies across the line range.

It would be possible to organize and allocate each passenger at the ideal time (and on the bus), avoiding crowds and, now in COVID-19 times, maintaining the appropriate social distance to contain the spread of contamination by the virus. This optimization would also result in other benefits such as reduced travel time, since it is possible to reduce the number of stops with time savings for users, reduced fuel consumption and, consequently, pollution levels, improved overall satisfaction citizens with the synchronization of their daily activities and time-saving commitments and avoiding crowds also in the places where these activities occur.

This project reiterates and strengthens connections with public transport management and SDC main concepts (Rezende, 2012, 2016, 2018) since the city can achieve its objectives, through a coordinated city strategy involving citizens, operators and all other involved organizations like schools, shops, factories and offices. All city information is available and, with the proper information technology resources, it's a matter to develop one app able to integrate and coordinate people's daily activities, taking in consideration other variables revealed in this study like day class, school day and climatic conditions. In this direction, the number of buses in the line can be optimized and loaded with the optimal capacity, respecting the COVID-19 pandemic issues, through a better distribution and coordination between public and services during the day. As the city can be divided into municipal themes (for example, transport and health) and the strategic digital city project is divided into 4 subprojects (city strategies; cities information; public services; and information technology resources application), these themes have related each other. Transport is emphasizing public vision and health directed towards the pandemic, connected through the resources of information technology.

The research contributions are directed to the strategic digital city project application also in the confrontation of pandemic crises. The study provides indications that the connection between these subprojects can help public managers not only to cope with an infectious disease that plagues the world but can also help them to reflect on the cities they manage and its respective long-term planning. It can even lead them to develop strategic planning anchored in the long-term city objectives rather than four-year-long government plans.

For the academic community, the research methodology, its qualitative and quantitative techniques and the respective research protocol, can be shared and experienced as models to another studies. For the research group on Strategic Digital City, this research reflects a practice of studies and realities in cities that can be used as an example for other researchers. And when it comes to research on public policies, it refers to another study that proves that SDC is also a public policy to assist managers in their public decisions regarding city planning and citizens in their decisions regarding their quality of life. Thus, the entire civil society can benefit from this research that expresses the reality of a city and its urban challenges.

6. Conclusion

Before the COVID-19 arrives in Brazil, Curitiba's bus public transportation system was transporting 1,36 million passengers per day in a working day. When the pandemic started and at the middle of March/2020 and social distancing measures went rigorous, the number of passengers went down in more than 80% and many bus lines was canceled. At the pandemic peak, the number of passengers per day was only in 200 thousand per day. Fleet on streets felt down as well and operators started to receive extra payments from municipality in order to maintain the service in an acceptable level and to avoid bankruptcy. When the contagious curve started to go down in mid of September/2020, almost all bus lines came back to operation but with reduced fleet (same used on Saturdays) but only with 70% of each car maximum capacity allowed (URBS, 2020).

If the attractiveness of public transportation was already critic before the pandemic due to passenger's losses to other transport modals, during the pandemic it turn to impossible. The system still operating only because the Municipality is paying the operators to have more buses during rush hours and to have buses almost empty in other day periods, revealing inefficiencies about how to coordinate demand and offer. Increasing fare price was also impracticable because there is, at least, 62% gratuity during rush hours.

The research results showed that about 90% of passengers are taking the same bus every day to work and to go to school and is possible to map where they live and take the bus and that is affected by climatic conditions, a very accurate urban management tool can arise and may be able to solve not only the pandemic issues but also to improve local public services efficiency, to attract private investments and to improve citizen's quality of life. The proposed research objective was achieved because is possible to have good public transport services, but it must be managed as a business, starting with a proper and deep audience definition and targeting, in order to offer benefits and advantages that other transport ways cannot do. A proper scaling and scheduling to connect people's daily activities can bring more comfort and safety not only during COVID-19 pandemic but can also give more free time for users with their routines synchronized, that is in accordance with SDC concept defined by Rezende (2012; 2016; 2018).

The SDC project and its respective subprojects are directly connected with cities management and to facilitate the citizens' quality of life, especially in public transport and in facing the pandemic. Since the city hall and public transport operators can electronically map where passengers live, work, study and access public and private services, it is recommended to create a smartphone application capable to organize, synchronize and indicate, in real time, which bus at which bus stop and at what time each passenger should take for their scheduled appointments, without exceeding the maximum recommended capacity per car, either due to pandemic issues or under normal operating conditions.

The application must include the monitoring of variables indicated by this study, such as the type of day of the week, weather conditions, school days and holidays in order to the municipality and the operators put into operation only the optimal number of cars that offer comfort and safety for passengers, adequate remuneration for system operators and efficiency for the services provided by the municipality, which also offer satisfaction to citizens.

The research limitation resides in the fact that only one main bus line was taken in consideration. More city bus lines must be studied and for a longer period of time to confirm not only the demand stability but also if the public transport attractiveness is losing passengers to other transport modals. Another limitation involves other important variables that must be tested as well, like fuel and bus fare prices, number of other vehicles, especially cars and motorcycles, and public investments in alternative ways of transportation like bicycle paths and the number of bikes.

The discussions described are relevant since transport is the bigger issue for workers and students, especially the least economically favored even outside pandemic periods. There are many other needed steps to advance but this study brought some interesting insights that can simplify and solve the majority of problems involving not only people overcrowding in the same space at the same time, but also one better coordination between citizens and public and non-public services, increasing satisfaction, comfort, efficiency and saving time and money.

Declaration of competing interest

None.

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