A DISCRETE-EVENT PUBLIC TRANSPORTATION SIMULATION MODEL TO EVALUATE THE IMPACTS OF SOCIAL DISTANCING AND TRAVEL DEMAND MANAGEMENT

Jaime Soza-Parra, Institute of Transportation Studies, University of California, Davis
jsozaparra@ucdavis.edu
Ignacio Tiznado-Aitken, Department of Human Geography, University of Toronto
i.tiznadoaitken@utoronto.ca
Juan Carlos Muñoz, Departamento de Ingeniería de Transporte y Logística,
Centro de Desarrollo Urbano Sustenable (CEDEUS),
Pontificia Universidad Católica de Chile jcm@ing.puc.cl

ABSTRACT

COVID-19 has generated significant mobility impacts in Santiago de Chile: mandatory and non-mandatory trips have declined by an average of 38% over the last year. Despite such a drop, a high share of low-income groups still relies on public transport for their daily activities. Thus, the decline is far from being homogeneous across socioeconomic groups. And due to the strong urban segregation observed in the city some flows have diminished significantly more than others. Thus, some services at certain periods present a quite high demand. In this scenario managing travel demand and public transport supply becomes key to keeping the number of people circulating in the system safe.

Our work develops a simulation tool of the operations of a public transport system to evaluate the impacts of different intervention scenarios in a pandemic context. Using a baseline scenario that severely violates safety and social distance recommendations, we study the impact of several travel demand and public transport supply measures, focusing the analysis on waiting times and crowding conditions inside vehicles and platforms. As a result, we generate easy-to-analyze visual outputs that can assist prioritizing actions at the metropolitan and district level.

Keywords: Public transport, Passive data, Discrete-event simulation, COVID-19

1. INTRODUCTION

COVID-19 has generated significant impacts on almost every dimension of our everyday lives. The pandemic has caused over 180 million contagions and almost 4 million deaths (WHO, 2021) and the International Monetary Fund (IMF) estimated a global economy shrunk of 4.4% in 2020. Besides health and economic impacts, countries worldwide have been restricting usual mobility patterns, imposing or recommending social distancing and quarantines in order to avoid contagion. First, on a global scale, international travel bans and regulations at points of entry were adopted. Then, governments and local authorities adopted mobility preventive measures at the national and local scale, changing how people accessed their activities and essential services.

As Gkiotsalitis & Cats (2021) noted, the gradually return to normality demands new public transport adjustments and related preventive measures, considering the impact on passenger demand and ridership levels, as well as the risk of virus transmission. These adaptions can be at strategic, operational or tactical levels. Given their nature, most strategic measures are not discussed to handle this sanitary crisis since they usually imply infrastructure investments or network redesign that take too long to implement. Still some cities have suspended or altered few existing services (UITP, 2020). On the tactical side, frequency changes for certain services (including fleet reallocation) is the most used strategy. Among operational measures, crowd management at stations, skip stations or boarding limits, which are widely studied in the literature have also been tried.

Severe transit ridership drops are happening all over the world. In Santiago, Chile, mandatory and non-mandatory transit trips have declined by an average of 38% over the last year. Education trips were completely suppressed as universities and schools stopped operating in a face-to-face format, while commuting has declined by 37% (Google, 2021) since the economic activity has declined and several employers allow their employees to work from home. Still, many workers must commute daily: informal street workers, formal workers lacking telecommuting facilities at home, public servants who had to go back to work due to the government's call for "new normality", etc (Vecchio & Tiznado-Aitken, 2020).

Despite public transport stations having declined their affluence by 44% (Google, 2021), a high share of low-income groups still rely on public transport for their daily activities. Since Santiago is a very segregated city in which most affluent sectors live in the northeast of the city, and this sector attracts most morning commute trips, the use of public transport vehicles has a clear and strong socioeconomic bias. While in one direction vehicles may move nearly empty, the other one could face crowdedness above sanitary recommendations due to marked demand unbalance. This strong unbalance is caused by the socioeconomic segregation observed in Santiago and increased by the opportunities for telecommuting which are mosly ejoyed by wealthy citizens. Thus, the commuting patterns predicted for Santiago during the pandemic will likely expose its low-income users the most to contagion exposure (Astroza et al., 2020). Indeed, Carranza et al. (2020) show that high-income groups reduce their mobility significantly more levels than low-income groups, which might be an important factor to explain contagion differences among municipalities in Santiago and is a matter of concern once mobility recovers closer to its pre-pandemic level.

According to Tirachini & Cats (2020), the proper use of face masks and hygiene standards as ventilation and sanitization has significantly reduced the probability of contagion. They have become the norm in Santiago's buses and trains. Public transport authorities should focus on preventing crowding from exceeding recommended levels at stations and vehicles, through increasing transport capacity in critical services and fostering traveling at off-peak periods (Arellana et al., 2020). Thus, managing both travel demand and public transport supply becomes key to keeping the number of people circulating in the system safe. Understanding where and when the crowding thresholds would be exceeded under different scenarios becomes a very relevant anticipatory tool to manage the system properly. Interestingly preventing crowding inside vehicles from exceeding critical levels would also improve users comfort which has a strong positive impact in their satisfaction.

Our work develops a simulation tool of the operations of a public transport system to evaluate the impacts of different intervention scenarios in a pandemic context. Using a pre-pandemic baseline scenario that severely violates safety and social distance recommendations, we study the impact of several travel demand and public transport supply measures, focusing the analysis on waiting times and crowding conditions inside vehicles and platforms. As a result, we generate easy-to-analyze visual outputs that facilitate prioritizing actions at the metropolitan and district level.

2. DATA AND METHODS

The methodology is structured around a discrete-event simulation model developed to represent the public transport system of Santiago under different demand and supply scenarios. The baseline scenario is based on 2019 public transport operation, before the social outburst in October 2019 that had a proofound impact in the city's mobility patterns, Thus, the scenario is previous to the COVID-19 pandemic which hit the city in March 2020. The origin-destination public transport demand is obtained from existing smart-card-based trip information (DTPM, 2019a). For each origin-destination, a set of possible public transportation routes is obtained from the observed trips in a given week. Then, trips are sampled from this database in order to represent a normal day of public transport demand. The supply is defined based on the available GTFS information, for both buses and trains (DTPM, 2019b). This information consists of the arrival time of each simulated vehicle to each stop along its route. This means the number of vehicles is not considered as a restriction of the simulation but as a result (which depends on the frequency of each service) and traffic congestion is exogenously addressed by historic travel times between stops. Thus, each simulated passenger follows its sampled public transport sequence of services and stops to reach their destination, boarding and alighting each service according to the simulated operation.

In order to correctly simulate the morning peak period, the simulation considers a warm-up period starting from 01:00 until 05:29, while the indicators released by the simulation are obtained from 05:30 until 12:00. The simulation of waiting passengers is structured as a set of queues at each bus stop and metro station, while passengers board their desired vehicle following a First-in-first-out (FIFO) scheme. In addition, each vehicle has a fixed and strict passenger capacity (in a non-pandemic context), which is 100 for buses (which corresponds to a weighted average between 80 and 160 people capacity buses) and between 1,300 and 1,600 for different metro lines. Transfer times were assumed null, meaning that people transferring between two different stops or stations enter the next queue instantaneously when the previous vehicle reaches the alighting stop.

Having the baseline simulated, each scenario is defined as a combination of different demand and supply conditions. Regarding the demand, different telecommuting probabilities are assumed as an indicator of the reduction of work and education purpose trips in the city. To do so, the model presented by Astroza et al. (2020) is used in combination with census data to describe each origin's sociodemographic information. Thus, we define the "pandemic" scenario, which considers a 100% reduction of educational trips and a 30% of workers telecommuting across the city (and heterogeneously distributed according to the aforementioned model and sociodemographic data), and a "transition" scenario which considers a 50% reduction in educational trips and a 15% telecommuting level (heterogeneously distributed too). Also, travel demand management (TDM) actions are considered in each one, to reduce crowdedness during peak periods. These TDM actions only consider an smoothness of the travel demand between 06:30 and 10:30 am and is applied regardless of travel purposes. Thus, this methodology only illustrates the potential benefits of travel demand management and does not consider how these travel demand redistribution might be applied. Regarding the supply, four additional scenarios are defined. These scenarios consider strictly reducing the number of passengers allowed to board to 30% and to 60% of the vehicle capacity in order to increase social distancing inside the vehicles. These two policies are combined with eltger keeping the frequency of every service as planned and incrementing them by 20%. The combination of these different attributes yield 30 scenarios which are described in Table 1.

Scenario	Public transport demand	Travel Demand Management (TDM)	Capacity	Frequency
1	Baseline	No	100%	Baseline
2	Baseline	No	60%	Baseline
3	Baseline	No	60%	Baseline + 20%
4	Baseline	No	30%	Baseline
5	Baseline	No	30%	Baseline + 20%
6	Pandemic	No	100%	Baseline
7	Pandemic	No	60%	Baseline
8	Pandemic	No	60%	Baseline + 20%
9	Pandemic	No	30%	Baseline
10	Pandemic	No	30%	Baseline + 20%
11	Transition	No	100%	Baseline
12	Transition	No	60%	Baseline
13	Transition	No	60%	Baseline + 20%
14	Transition	No	30%	Baseline
15	Transition	No	30%	Baseline + 20%
16	Baseline	Yes	100%	Baseline
17	Baseline	Yes	60%	Baseline
18	Baseline	Yes	60%	Baseline + 20%
19	Baseline	Yes	30%	Baseline
20	Baseline	Yes	30%	Baseline + 20%
21	Pandemic	Yes	100%	Baseline
22	Pandemic	Yes	60%	Baseline
23	Pandemic	Yes	60%	Baseline + 20%
24	Pandemic	Yes	30%	Baseline
25	Pandemic	Yes	30%	Baseline + 20%

26	Transition	Yes	100%	Baseline
27	Transition	Yes	60%	Baseline
28	Transition	Yes	60%	Baseline + 20%
29	Transition	Yes	30%	Baseline
30	Transition	Yes	30%	Baseline + 20%

Table 1. Scenarios tested in our public transport simulation

The simulation outputs are characterized in three different levels. First, for each simulated trip, we obtain its waiting and travel times and the density distribution experienced at each trip-leg. Second, for each stop or station in the system, the distribution of waiting times and queue lengths are computed for each one-hour period. Third, for each service, direction, pair of consecutive stops, and one-hour period, the distribution of passenger density inside the vehicles is calculated.

3. EARLY RESULTS

Our work generates a useful visualization of the impacts of each scenario that should be valuabkle for orienting strategic interventions on Santiago's public transport system. Since the system involves over ten thousand bus stops, one hundred Metro stations and thousands of vehicles, stop we provide an aggregated view of the system. Thus, instead of visualizing the conditions yielded for each bus stop or Metro station, we divide the Greater Santiago area into 784 cells using a hexagonal grid of 1000 meters each. In each cell we provide performance indicators as the number of people waiting or waiting times yielded by the simulation of each scenario. Figure 1 shows a proof of concept where the 80th percentile of the total number of people waiting at each bus stop is contrasted with the visualization obtained at the hexagon level for the baseline simulation case. The cell-based tool allows us to easily identify where the biggest challenges are predicted in terms of crowding at stops for each scenario.

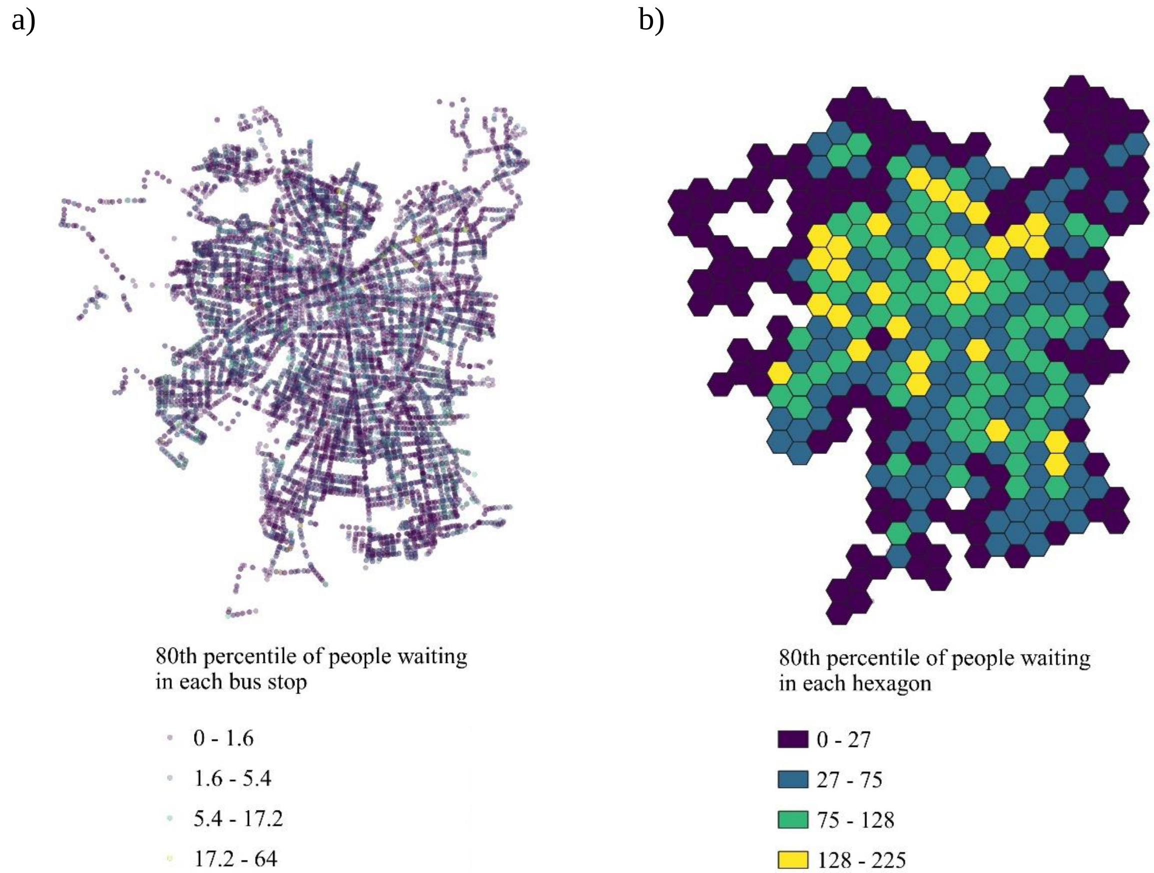

Figure 1. 80^{th} percentile of people waiting in a) each bus stop b) each hexagon

Our work also considers a novel visualization tool for passenger density in the entire network by aggregating the outputs of the simulation model into the previously designed hexagonal grid. The purpose is to quickly identify the most critical locations across the city in terms of social distancing, and thus, being able to allocate efforts and resources efficiently. This is of the utmost importance in an emergency context as resources are limited, especially in developing countries. To do so, for every pair of adjacent hexagons (A and B in Figure 1), we calculate the average passenger density in a virtual arc that includes all services circulating from A to B (in that direction) considering every service arc between every pair of stops where either both are located inside hexagon A, one is located in hexagon A and the other in hexagon B, or both are inside hexagon B.

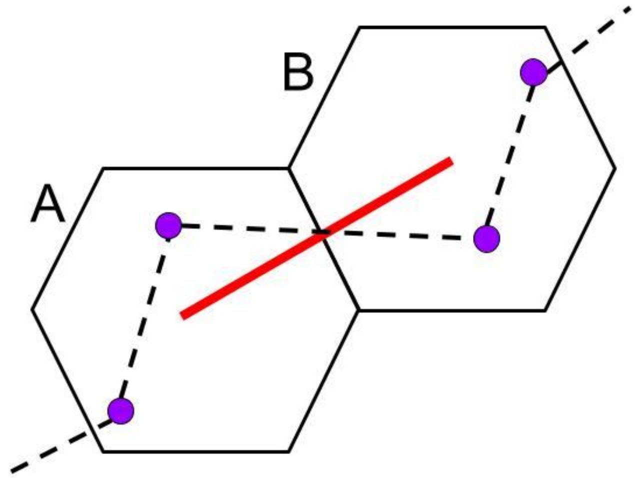

Figure 2. Process to calculate the average density between two hexagons

As in the previous case, we made a proof of concept of this visualization using the results of the baseline simulation case. The comparison between Figures 3a and 3b (which differentiates trips moving north and east from those moving south and west) show clearly that the the most crowded in terms of passenger density happens traveling towards the northeast of the city where the most affluent sectors live and where the concentration of job opportunities is the highest, particularly the Providencia, Santiago and Las Condes municipalities. In contrast, the south and westbound direction is not highly loaded except within the Santiago municipality, associated to the traditional center of the city. Although not analyzed here, this scenario would be overall reversed when analyzing the afternoon peak period. Again, this form of visualization allows to identify which areas of the city should be prioritized for intervention in a pandemic context that reconfigures the demand levels, and provides opportunities to adjust frequencies and vehicle capacities to satisfactorily address the social distance within public transport.

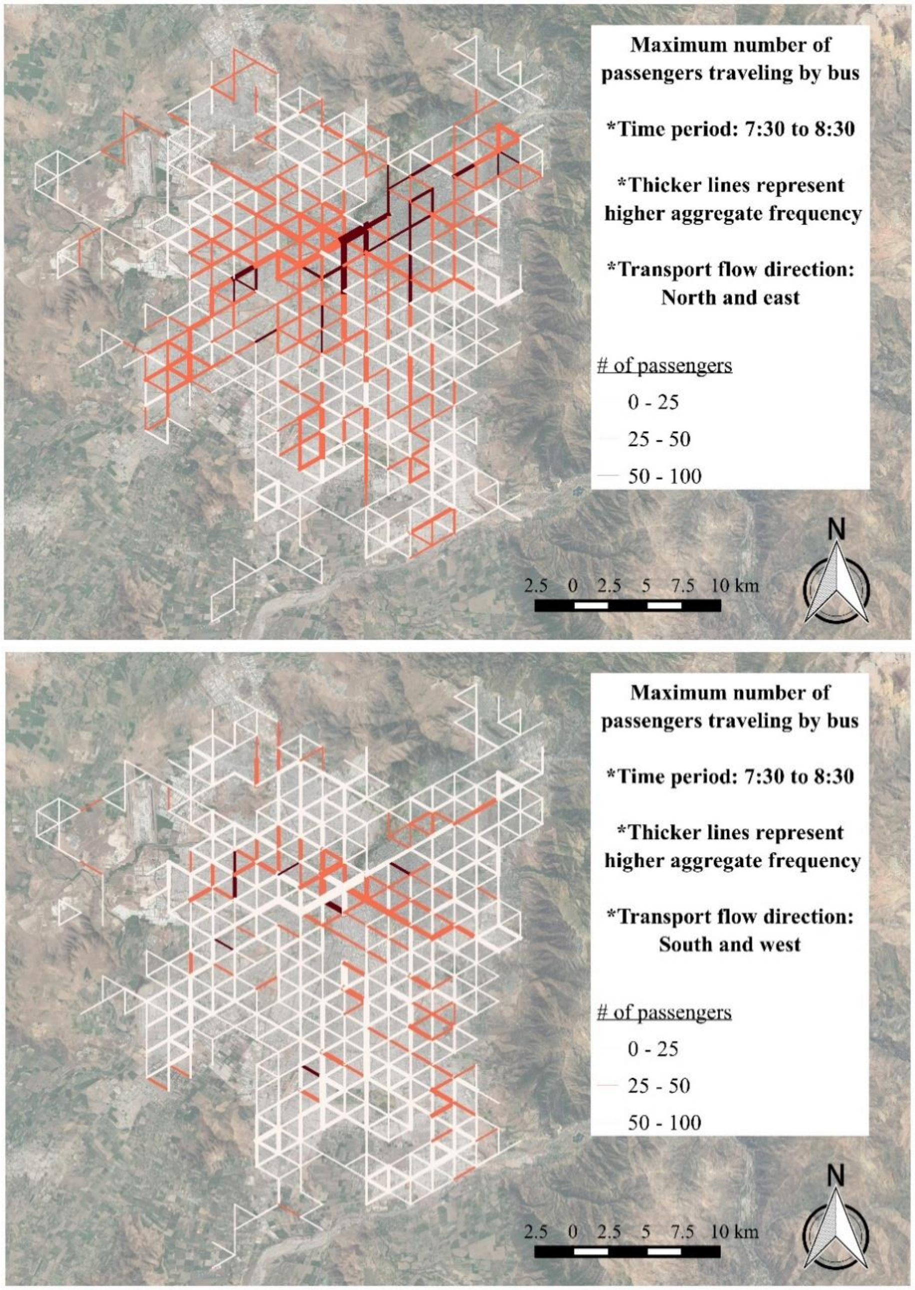

Figure 3. Maximum number of passengers traveling by bus for a) North and East direction, b) South and West.

Early results in terms of waiting times and passenger density impacts for scenarios where TDM is not implemented are presented in Figure 4. We see that, overall, telecommuting has a significant improvement in the level of service experienced by passengers in the simulation mostly because of the reduction of travel in those scenarios. However, we see that in the baseline scenario more than one-half of the passengers experience more than 1 passenger per square meter, while around one-quarter of them experience a passenger density exceeding 3 pax per square meter. We also see that limiting the number of passengers to 60% of the capacity of the vehicle has a non-significant effect on the density over 1 pax/m2 if the frequency is not increased. By limiting the number of passengers boarding to 30% with a 20% frequency increase, we see that only 20% of passengers experience an average density over 1 pax/m2, none over 3 pax/m2, but total waiting times double.

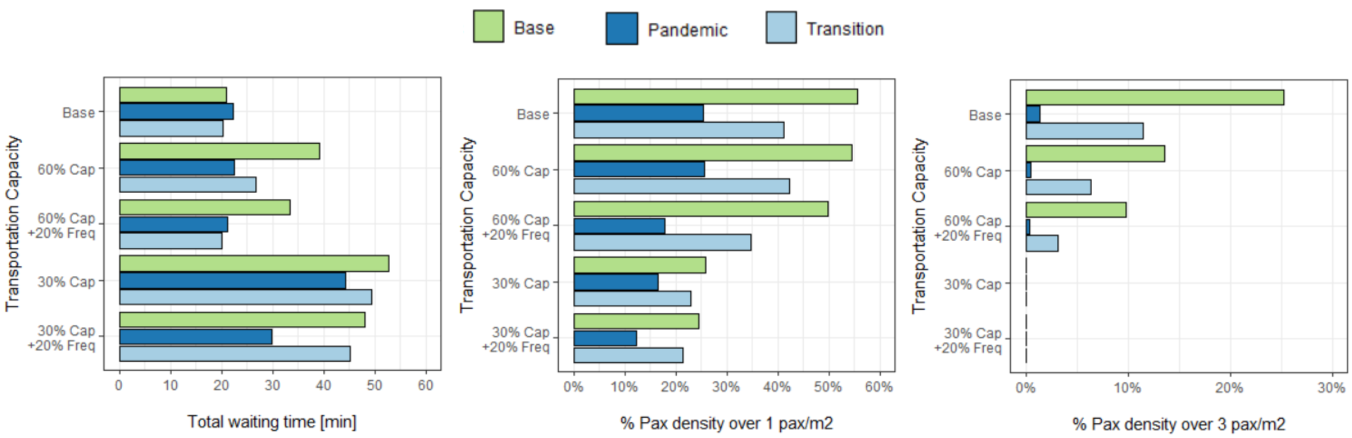

Figure 4 Results of the simulation model in terms of a) Total waiting time and % of passengers experiencing over b) 1 pax/m2 and c) 3 pax/m2

Table 2 displays a summary of these results including the absolute and relative impact of travel demand management (TDM). Each column represents each of the three performance indicators (average total waiting time, % of trips with passenger density over 1 pax/m^2 and 3 pax/m^2). Overall, we see how travel demand management improves the level of service experienced by the passengers. As expected, large relative changes due to TDM are mostly associated with low nominal values. We see how for the pandemic demand scenario, travel demand management has a reduced effect, as it is not necessary to accomplish similar waiting times to the baseline and a controlled passenger density if transportation capacity is limited to a 60%. Optimum results in terms of reduced passenger density are obtained when limiting transporation capacity to a 30% and increasing the offered frequency by 20%. However, under this scenario waiting times double. Only by managing travel demand, waiting times become similar to the baseline in the pandemic scenario and less than doubled in the transition scenario. Considering this tradeoff between waiting times and passenger density and the difficulty in increasing frequency through out the entire city, the preferred scenario this simulation suggests considers a 60% in transportation capacity and travel demand management. In this scenario, total waiting times are no more than 6 minutes longer than the baseline, only 17% of passengers experience over 1 passenger per square metre during the pandemic scenario, and 41% do during the transition scenario.

			Total waiting time			% Pax density over 1 pax/m²			% Pax density over 3 pax/m²		
		Demand	**No TDM**	**With TDM**	**Change**	**No TDM**	**With TDM**	**Change**	**No TDM**	**With TDM**	**Change**
Transportation Capacity	Base	Base	20.9	19.9	-5%	56%	56%	1%	25%	23%	-9%
		Pandemic	22.4	21.7	-3%	25%	17%	-35%	1%	1%	-19%
		Transition	20.4	20.2	-1%	41%	41%	-1%	11%	6%	-46%
	60% Cap	Base	39.2	36.3	-7%	54%	54%	0%	14%	12%	-8%
		Pandemic	22.5	21.7	-3%	26%	17%	-35%	1%	0%	-28%
		Transition	26.7	22.4	-16%	42%	41%	-3%	6%	4%	-36%
	60% Cap + 20% Freq	Base	33.5	30.3	-10%	50%	50%	-1%	10%	9%	-13%
		Pandemic	21.2	20.4	-4%	18%	9%	-50%	0%	0%	-10%
		Transition	20.2	19.1	-5%	35%	33%	-6%	3%	1%	-60%
	30% Cap	Base	52.8	50.1	-5%	26%	25%	-2%	0%	0%	-
		Pandemic	44.3	32.3	-27%	17%	12%	-25%	0%	0%	-
		Transition	49.3	43.8	-11%	23%	22%	-5%	0%	0%	-
	30% Cap + 20% Freq	Base	48.0	45.7	-5%	24%	24%	-1%	0%	0%	-
		Pandemic	30.0	23.1	-23%	12%	7%	-43%	0%	0%	-
		Transition	45.3	39.7	-12%	22%	20%	-8%	0%	0%	-

Table 2. Simulation results and transportation demand management impact.

4. CONCLUSIONS AND FUTURE WORK

Our work develops a simulation tool of the operations of a public transport system to evaluate the impacts of different intervention scenarios in a pandemic context. We made a proof of concept of the tool, evaluating the baseline scenario in terms of people waiting and user density within vehicles using a novel visualization based on a hexagonal grid. As a result, we generate easy-to-analyze visual outputs that facilitate prioritizing actions at the metropolitan and district level.

As future work, it is expected to compare the impact of the different simulated scenarios in terms of vehicle density and users waiting at public transport stops. This will allow to focus the efforts of strategic management of public transport, compensating with higher frequencies the highly overcrowded zones, allowing a greater physical distance among users inside the vehicles. By using hexagons as a form of visualization, intervention can be focused into a set of desirable stops or routes , which can also help better coordinating with local authorities for proper operation.

ACKNOWLEDGMENTS: This research was supported by the Centro de Desarrollo Urbano Sustentable, CEDEUS (Conicyt/Fondap 15110020).

REFERENCES

Arellana, J., Márquez, L., & Cantillo, V. (2020). COVID-19 Outbreak in Colombia: An Analysis of Its Impacts on Transport Systems. Journal of Advanced Transportation, 2020.

Astroza, S., Tirachini, A., Hurtubia, R., Carrasco, J.A., Guevara, A., Munizaga, M., Figueroa, M., and Torres, V.. (2020). Mobility Changes, Teleworking, and Remote Communication during the

COVID-19 Pandemic in Chile. Transport Findings. https://doi.org/10.32866/001c.13489.

Carranza, A., Goic, M., Lara, E., Olivares, M., Weintraub, G. Y., Covarrubia, J., ... & Basso, L. J. (2020). The social divide of social distancing: Lockdowns in santiago during the covid-19 pandemic. Available at SSRN 3691373.

DTPM (2019a). Travel Matrices for Santiago. Available at: https://www.dtpm.cl/index.php/documentos/matrices-de-viaje

DTPM (2019b). Santiago DTPM GTFS. Available at: https://transitfeeds.com/p/dtpm-santiago-santiago/972

Gkiotsalitis, K., & Cats, O. (2021). Public transport planning adaption under the COVID-19 pandemic crisis: literature review of research needs and directions. Transport Reviews, 41(3), 374-392.

Google (2021). COVID-19 Community Mobility Report for Chile. Available at: https://www.google.com/covid19/mobility/
Tirachini, A., & Cats, O. (2020). COVID-19 and Public Transportation: Current Assessment, Prospects, and Research Needs. Journal of Public Transportation, 22(1), 1.

UITP. (2020b). Public transport authorities and COVID-19: impact and response to a pandemic. Retrieved May 30, 2020, from https://www.lek.com/sites/default/files/PDFs/COVID19-public-transport-impacts.pdf

Vecchio, G., & Tiznado-Aitken, I. (2020). (Im)Mobility and Health in Santiago de Chile. Journal of Latin American Geography, 19(3), 240-247.

WHO (2021). World Health Organization: Coronavirus Disease (COVID-19) Dashboard. Available at: https://covid19.who.int/