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A discrete-event public transportation simulation model to evaluate travel demand management impacts on waiting times and crowding conditions

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ABSTRACT

Several approaches have been proposed and adopted by researchers and decision-makers to improve and deal with public transport operation issues, especially travel demand management (TDM) measures. Disruptions like lockdowns provoked by weather conditions, political riots, special events, natural disaster issues, or the recent COVID-19 pandemic create a need for tools to manage public transport demand and supply o keep users circulating in an efficient, convenient and safe manner. Our work develops a simulation tool of the operations of a public transport system using smart card, GTFS and census data to evaluate the impacts of different intervention scenarios using the pandemic context as a case study. Using a pre-pandemic baseline scenario, 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, identifying where and when waiting times and crowding conditions would exceed certain thresholds.

1. Introduction

Providing a high-quality public transport system builds loyalty among current public transport users and has the capacity to attract users from other modes of transport. Key features are not limited to low walking, waiting, and in-vehicle times but also to safety, reliability, and comfort. Therefore, public transport operators and agencies face important challenges in managing and providing efficient and quality service (Ojo, 2019).

The literature has focused on a wide range of public transport operation issues, ranging from theoretical contributions as microeconomic models aiming at optimizing frequency and capacity under crowding constraints (Jara-Díaz & Gschwender, 2003) to data-driven and simulation approaches for bus dwell time at stops (Fourie et al., 2016). These approaches allow researchers and decision-makers to improve and deal with public transport operation issues, for example, through travel demand management (TDM) measures.

Most TDM measures focus on reducing the impact of private and individual transport (Loukopoulos, 2007), aiming at modifying the behavior and habits of travelers to maximize more efficient and clean modes of transport. However, given the nature of public transport and demand concentration during morning and afternoon peak hours, public transport TDM-focused measures have been dealing with peak spreading. Certainly, peak spreading involves trade-offs between demand and supply. Daniels & Mulley (2013) pointed to potential reductions in frequency and fewer express services when spreading the peak over a wide period, making public transport less attractive.

Peak spreading seemed like an interesting and effective measure in the early days of the pandemic. The scenario was characterized by a high decrease in public transport demand, considering the 158 days (about five months) schools closed on average (UNICEF, 2021) and 23 million people teleworking (ILO, 2021) in the Latin American context. Additionally, both mandatory and non-mandatory transit trips declined by an average of 38 % in 2020, with a 44 % affluence drop in public transport stations (Google, 2021) in Santiago, Chile. However, the need for social distancing to avoid contagion created a proposal around peak spreading through different timings for activities like work, education, or leisure and providing both in-vehicle and platform crowding information (Tirachini & Cats, 2020). Public transport authorities should focus on preventing crowding from exceeding recommended levels at stations and vehicles by increasing transport capacity in critical services and fostering traveling during off-peak periods (Arellana et al., 2020). Thus,

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managing both travel demand and public transport supply becomes crucial in keeping the number of people circulating in the system safe.

As Gkiotsalitis & Cats (2021) noted, the gradual 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 needed adaptations can be at strategic, operational, or tactical levels. Given their nature, most strategic measures are not discussed to handle the short-term effects of this sanitary crisis since they usually imply infrastructure investments or network redesign that take too long to implement. On the tactical and operational side, some cities have suspended or altered routes and frequencies of few existing services, including fleet reallocation. Furthermore, crowd management at stations, skip stations, or boarding limits, which have been widely studied in the literature, have also been tested (UITP, 2020; Gkiotsalitis & Cats, 2021).

The question we address in this paper is how the public transport system would react to different demand and operational policies aiming at guaranteeing the reduction of waiting times and crowding conditions. Our work develops a simulation tool of the operations of a public transport system using smart card, GTFS and census data to evaluate the impacts of different intervention scenarios using the pandemic context as a case study. As Gaudette et al. (2016) discussed, combining these types of datasets provides highly detailed representations of the public transport operation. Using a pre-pandemic baseline scenario, 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, identifying where and when crowding conditions inside vehicles and platforms would exceed certain thresholds. Our article contributes to an existing body of literature connecting public transport operations and COVID-19 (Qian & Ukkusuri, 2021; Mo et al., 2021; Gkiotsalitis & Cats, 2022; Singh et al., 2023) by testing different operational policies in public transport using a pandemic scenario in Santiago, Chile as case study. Our approach considers capacity under different scenarios and crowding inside vehicles and bus stops, contributing a different perspective of mixed-integer programming aiming at optimal frequencies with imposed capacities (de Weert, and Gkiotsalitis, 2021). Thus, we present an efficient way to predict critical locations from a passenger perspective by analyzing aggregate visualizations for different simulated scenarios.

The remainder of the article is structured as follows. Section 2 provides a detailed overview of the data and methods used for our study. Section 3 explains our visualization approach and how this can be useful for quick decision-making. Section 4 discusses the main findings, and finally, Section 5 discusses key takeaways for policy and research directions.

2. Background

2.1. A high level overview of the academic evidence around public transportation

Public transport is a subject widely studied internationally and from various academic disciplines. Multiple review articles serve as proof of these wide contributions surrounding the public transportation field. These contributions cover a broad spectrum of subjects, including areas such as transport economics (Hörcher & Tirachini, 2021) and transport geography (Saif et al., 2019). They also encompass a diverse range of impacts associated with public transport use and operation, such as its effects on traffic congestion and air quality (Beaudoin et al., 2015), its impact on physical activity (Rissel et al., 2012), and its influence on social capital (Currie & Stanley, 2008). The level of service provided by public transport has been evaluated from various perspectives, including service quality (Redman et al., 2013), issues related to crowding (Li & Hensher, 2013), and passenger satisfaction and loyalty (Van Lierop et al., 2018).

Additionally, some studies have a specific focus on population groups and the challenges they face when using public transport, such as women (Smith, 2008), older adults (Shrestha et al., 2017), and individuals with mobility and cognitive impairments (Unsworth et al., 2021; Risser et al., 2015). More recent contributions have concentrated on data sources, with a particular emphasis on emerging data sources (Zannat & Choudhury, 2019), big data (Welch & Widita, 2019), and smart card data (Pelletier et al., 2011). Finally, studies also delve into operational issues associated with public transport, such as addressing homelessness (Ding et al., 2022) and combating fare evasion (Barabino et al., 2020).

Our study focuses on how public transport can improve its performance through operational improvements. The literature has focused on a wide range of public transport operation issues, ranging from theoretical contributions as microeconomic models aiming at optimizing frequency and capacity under crowding constraints (Jara-Díaz & Gschwender, 2003) to data-driven and simulation approaches for bus dwell time at stops (Fourie et al., 2016). These approaches allow researchers and decision-makers to improve and deal with public transport operation issues, for example, through travel demand management (TDM) measures.

Most TDM measures focus on reducing the impact of private and individual transport (Loukopoulos, 2007), aiming at modifying the behavior and habits of travelers to maximize more efficient and clean modes of transport. However, given the nature of public transport and demand concentration during morning and afternoon peak hours, public transport TDM-focused measures have dealt with peak spreading. Certainly, peak spreading involves trade-offs between demand and supply. Daniels & Mulley (2013) pointed to potential reductions in frequency and fewer express services when spreading the peak over a wide period, making public transport less attractive. Peak spreading seemed like an interesting and effective measure in the early days of the pandemic, as seen in the following subsection.

2.2. COVID-19 and the challenges for public transport operation

The onset of the COVID-19 pandemic brought different social distancing measures and stay-at-home calls in order to avoid further contagion. Transportation was amongst the most affected life domains, and public transport services were significantly impacted by a sharp decline in ridership and regulations that reduced service capacity. The need to maintain high levels of service while ensuring safe distance was, therefore, a major challenge (Gkiotsalitis & Cats, 2021).

In Latin America, the scenario was characterized by a high decrease in public transport demand, considering the 158 days (about five months) schools closed on average (UNICEF, 2021) and 23 million people teleworking (ILO, 2021). Additionally, both mandatory and non-mandatory transit trips declined by an average of 38 % in 2020, with a 44 % affluence drop in public transport stations (Google, 2021) in Santiago, Chile. However, the need for social distancing to avoid contagion created a proposal around peak spreading through different timings for activities like work, education, or leisure and providing both in-vehicle and platform crowding information (Tirachini & Cats, 2020). Public transport authorities should focus on preventing crowding from exceeding recommended levels at stations and vehicles by increasing transport capacity in critical services and fostering traveling during off-peak periods (Arellana et al., 2020). Thus, managing both travel demand and public transport supply becomes crucial in keeping the number of people circulating in the system safe.

As Gkiotsalitis & Cats (2021) noted, the gradual 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 needed adaptations can be at strategic, operational, or tactical levels. Given their nature, most strategic measures are not discussed to handle the short-term

effects of this sanitary crisis since they usually imply infrastructure investments or network redesign that take too long to implement. On the tactical and operational side, some cities have suspended or altered routes and frequencies of few existing services, including fleet reallocation. Furthermore, crowd management at stations, skip stations, or boarding limits, which have been widely studied in the literature, have also been tested (UITP, 2020; Gkiotsalitis & Cats, 2021). Our paper examines how the public transport system would respond to various demand and operational policies aimed at reducing waiting times and overcrowding using a simulation tool with several data sources, as described in the following section.

3. Data and methods

The methodology is structured around a discrete-event simulation model developed to represent the number of passengers in each vehicle of the public transport system of Santiago under different demand and supply scenarios and then visualizing the results. Below we describe each stage in detail.

3.1. Public transport supply and demand simulation

Public transport operation is usually modeled through microscopic and mesoscopic models. The first approach is useful when a high level of detail is required, for example, to analyze stop operations from a traffic perspective (Fernández, 2010). Mesoscopic models can be a suitable alternative to evaluate operation planning and control by representing individual vehicles and movement with less computational effort (Cats et al., 2010).

For travel demand modeling, two main approaches can be found in the literature: trip-based and activity-based. In the first one, trips are used as the unit of analysis with the traditional four-step model (generation, distribution, mode choice, and assignment). The second one is based on the idea that travel is derived from activity participation, which faces different personal and social constraints (Chu et al., 2012). Popular software and tools such as MATSim (Balmer et al., 2009) or TRANSIMS (Smith et al., 1995) adopt an agent-based transport demand simulation considering multiple agents at highly disaggregated temporal resolution.

During the pandemic, different approaches have been applied: data-driven agent-based simulation framework in the Victoria line on the London Underground (Singh et al., 2023), time-varying weighted public transport encounter network to model the spreading of infectious diseases using smart card data (Mo et al., 2021) and a mixed-integer quadratic programming model for the redesign of public transport services (Gkiotsalitis & Cats, 2021).

Our approach for the simulation used a fixed origin-destination public transport demand 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. Each route corresponds to a sequence of Metro and/or bus services. Then, trips are sampled from this database in order to represent a normal day of public transport demand. Thus, this is the only source of randomness in the simulation, which can be controlled by keeping the sampled routes fixed in different scenarios.

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 that the number of vehicles is not considered as a restriction of the simulation but as a result, which depends on the frequency planned for each service and the cycle time assumed for each one. Traffic congestion is exogenously addressed through historical travel times between stops. Thus, this is the only element affecting headways along each route which tends to stay rather constant. In this scenario, each simulated passenger follows its sampled public transport sequence of services and stops to reach the destination, boarding and alighting the first arriving bus (with enough capacity) of each service. Notice that this method prevents us from considering a more realistic behavior in which users take the first bus from a set of services considered attractive for the trip leg. Since the route sample is obtained from real data, the assignment to the routes yielded by the simulation should be quite similar to the case in which users behave more realistically. Still, under this behavior, the simulated waiting times would be higher than in reality.

To correctly mimic 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 only from 05:30 until 12:00. The simulation of waiting passengers at each bus stop and metro station is structured as a queue, following a First-in-first-out (FIFO) scheme to board their desired vehicle. In addition, each vehicle is assumed to have a fixed and strict capacity (in a non-pandemic context) of 100 passengers for buses (which corresponds to an approximation of the average capacity of buses in Santiago since most have a capacity of 80 and few articulated buses have a capacity of 160 people) and between 1300 and 1600 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 incoming vehicle reaches the alighting stop. A schematic representation of the simulation process is depicted in Fig. 1. In simple terms, stops are the nodes where passengers form queues, and vehicles of different routes connect different stops to transport passengers to their desired destinations. The set of outputs from the simulation is then post-processed, as explained later in the article.

3.2. Scenarios

The baseline scenario (“No change”) is based on the public transport operation before the COVID-19 pandemic, which hit the city in March 2020. We used the available GTFS information from the operation immediately before the social outburst in October 2019, which had a profound impact on the city’s mobility patterns. The smart-card data also corresponds to 2019, in order to match demand and operation. Having the baseline simulated, each scenario is defined as a combination of different demand and supply conditions.

Regarding the demand side, we were inspired by the early start of the pandemic. Different telecommuting probabilities were estimated as an indicator of the reduction of work and education-purpose trips in the city. To do so, the binary Probit model presented by Astroza et al. (2020) is combined with census data (INE, 2017). This model allows us to describe how much telecommuting is expected depending on the sociodemographic characteristics of each municipality. Using data from an online survey during the last week of March 2020 (N = 4395), the authors investigated “Work from home during Week 2″ as the dependent variable, where Week 1 is considered “normal” (before the pandemic) and Week 2 as the first week of a nationwide response to COVID-19 in Chile. Table 1 shows the model coefficients, which let us estimate a z-score for each municipality. Then, we transformed the obtained z-score into a probability of telework using the inverse cumulative distribution of the standard normal distribution.

Given the inability to estimate the percentage of formal independent and informal workers at the municipal level, we used the average for the whole city in 2019 (INE, 2019). Moreover, considering the lack of income data in the Census and the relevance for the model, we inferred the socioeconomic groups using the *Indice Socio Material Territorial* (ISMT), which by using educational level (head of household), living conditions and housing quality from the Census, computes the spatial distribution of socioeconomic groups in Santiago (OCUC, 2018). We estimated how the different ISMT categories fit the survey ranges using the overall socioeconomic groups (SEG) classification and Santiago’s income distribution.

Using the output of the model, we were able to define two different scenarios. First, the “pandemic” scenario, which considers a 100 % reduction of educational trips and a 30 % of workers telecommuting

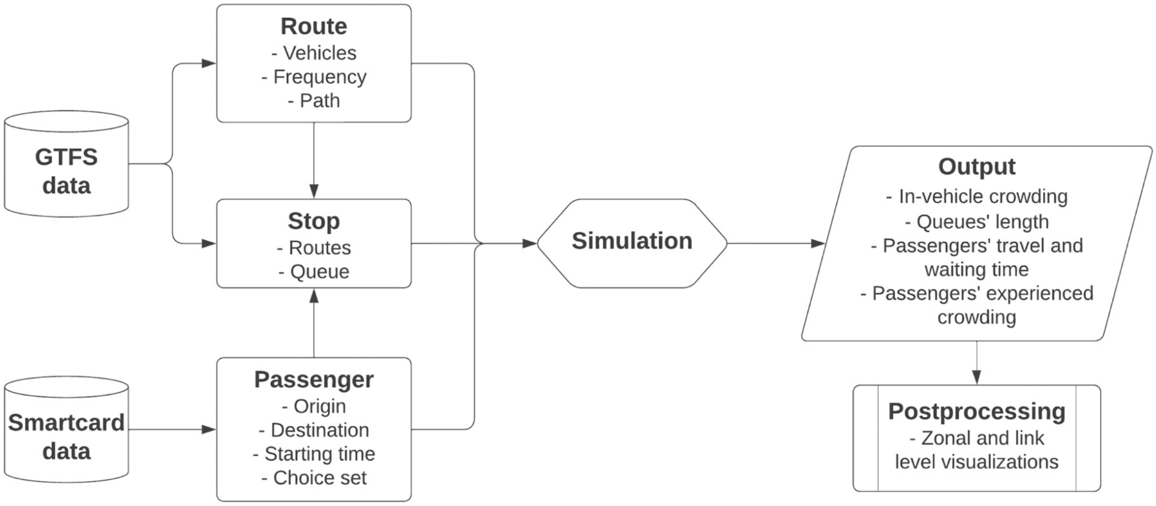

Fig. 1. Simulation diagram.

Table 1
Binary Probit model coefficients used to estimate the probability of telework for each municipality.

Category	Variable	Coefficient
	Constant	-0.3529
Gender (base is Male)	Female	0.3498
Age range (base is Between 18 and 25 years old and Between 36 and 45 years old)	Between 26 and 35 years old	0.1461
Educational attainment (base is High-school or less)	University degree	0.4909
	Post-graduate degree	0.6844
Household income [USD/month] (base is Less than 710)	Between 710 and 1180	0.2209
	Between 1180 and 1775	0.3657
	Between 1775 and 3550	0.6821
	Income of more than 3550	0.7081
Employment status (base is Formal dependent worker)	Formal independent worker	0.3046
	Informal worker	0.395
Essential worker status (base is Not an essential worker)	Healthcare worker	-1.6931
	Another basic service worker	-0.8064
	Household size	-0.0397

(Source: Own elaboration based on Astroza et al. (2020).

across the city, is heterogeneously distributed according to the aforementioned model. Second, a “transition” scenario which considers a 50 % reduction in educational trips and a 15 % telecommuting level, is also heterogeneously distributed according to the model. Thus, the total reduction in travel was calculated using origin-destination data, which gave us the percentage of work and educational trips at the municipal level. We assumed that trips made for other purposes remain the same as the “No change” scenario. Although the pandemic inspires the case study, these and other scenarios could be inspired by lockdowns provoked by weather conditions, political riots, special events or natural disasters.

Travel demand management (TDM) actions were assumed in each scenario to help reduce crowdedness during peak periods. These TDM actions, which affect the time when trips take place, are assumed to smooth travel demand between 06:30 and 10:30 am affecting all trips regardless of travel purposes. Thus, this methodology only illustrates the potential benefits of travel demand management, and we do not discuss how to foster this travel demand redistribution. Specifically, we distributed the total number of trips during the mentioned time window by weighting it by the square root of the quotient of the observed number of trips and the average. This calculation made the managed demand scenario follow the original’s shape and not necessarily the actual application of travel demand strategies. By doing this, we keep the total number of trips constant by decreasing it during the peak periods but increasing it outside. The comparison between the baseline when applying TDM is presented in Fig. 2. As can be seen, the purple bars under the TDM scenario follow the original shape but in a less steep way. Thus, the six possible demand scenarios are presented in Fig. 3).

On the supply side, four scenarios were defined. These scenarios consider enforcing the number of passengers allowed to board not to exceed 30 % and 60 % of the vehicle capacity in order to reduce crowding inside the vehicles. It is important to remember that, as the simulation runs in a FIFO, the only negative effect of these measures is an increase in waiting times. These two policies are combined to keep the frequency of every service as planned and increment them by 20 %. The 20 % value is picked arbitrarily as a thought experiment, as increasing the frequency of all services in a city by such an amount is unfeasible. A better depiction of what would happen would be to consider different frequency adjustments for every single line, but such optimization was considered to be out of the scope of our research. However, this 20 % increase can shed light on the extent increasing the frequency can balance the additional costs due to reduced capacity. Therefore, combining these different supply and demand attributes yields 30 scenarios described in Table 2.

Each simulation output was characterized in three different levels. First, for each simulated trip, we obtain its waiting and travel time and the average number of passengers distribution experienced inside the vehicle at each trip leg. Second, for each stop or station in the system, the distribution of waiting times and queue lengths were computed for each one-hour period. Third, for each service, direction, pair of consecutive stops, and one-hour period, the distribution of the number of passengers inside the vehicles was calculated. Considering the difficulty of visually representing all these results in a simple way, we concentrate on aggregate results of number of people waiting and flows of passengers traveling, as detailed in the following section.

3.3. Visualization

Our work provides a useful visualization of the impacts of each scenario that should be valuable for orienting strategic interventions on Santiago’s public transport system under a pandemic-like scenario. Easily visualizing the location of the main concerns in a city of over ten thousand bus stops and thousands of vehicles is not simple.

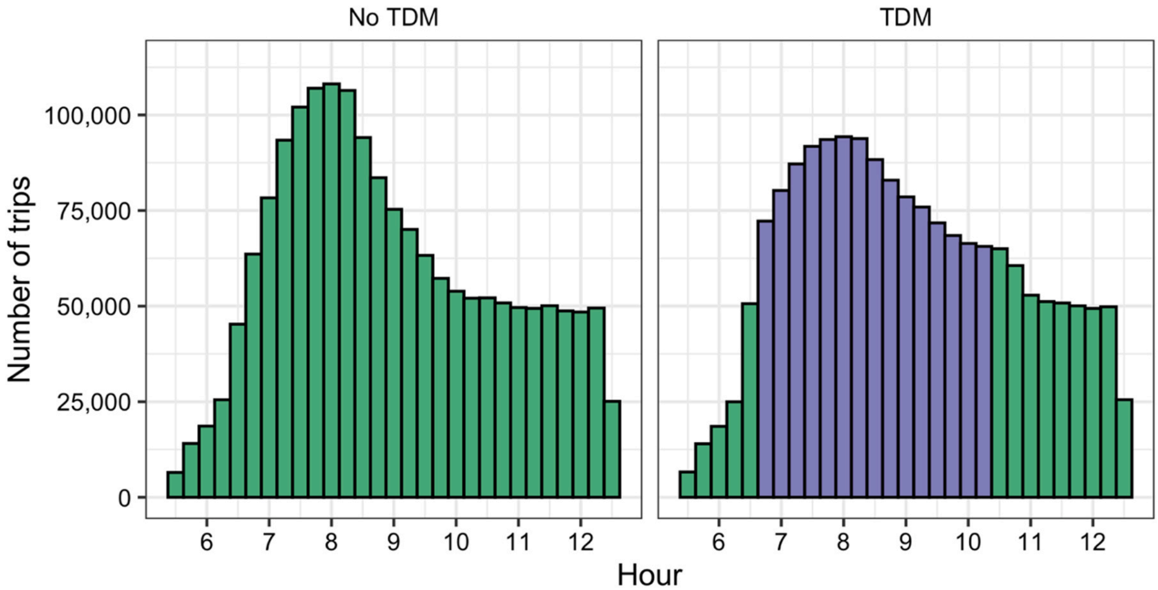

Fig. 2. Resulting transportation demand after applying Travel Demand Management (TDM).

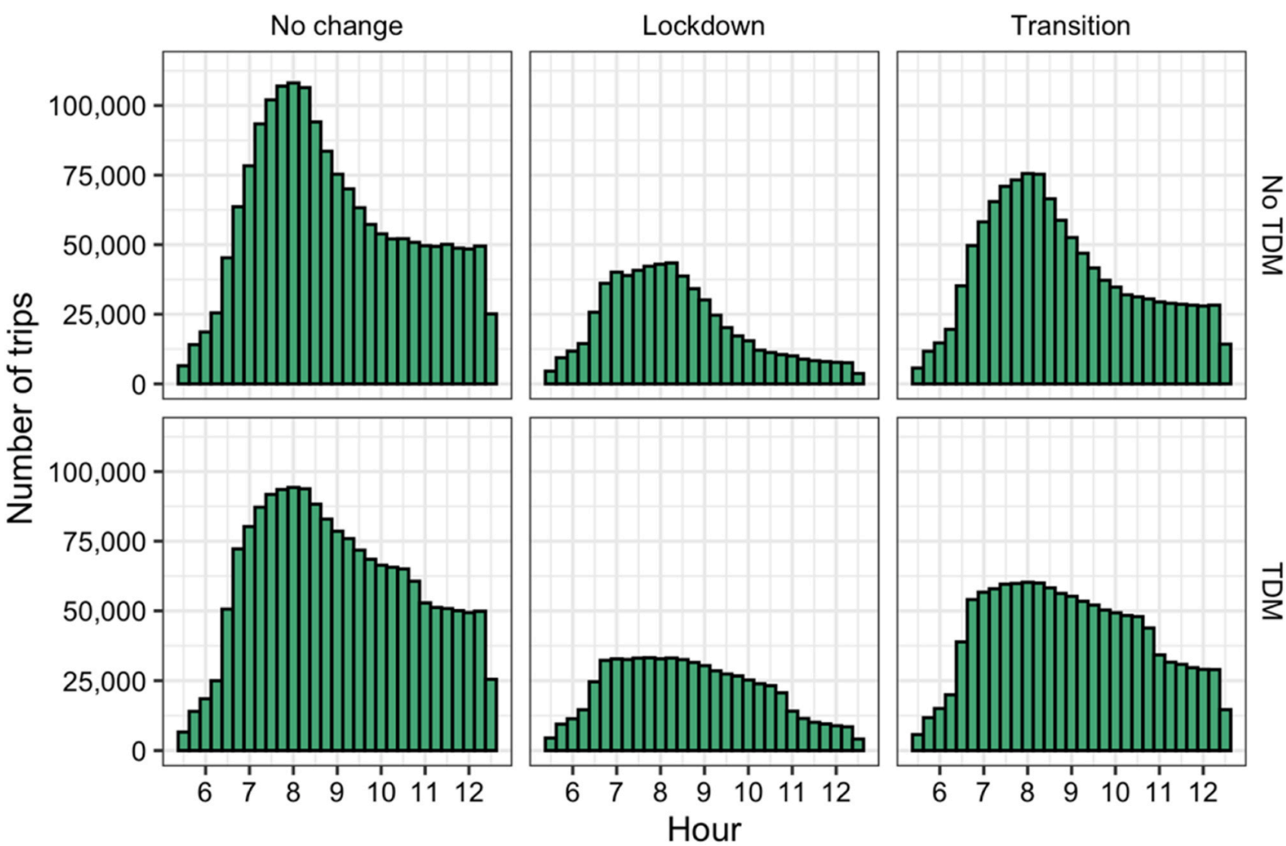

Fig. 3. Simulated demand scenarios.

Furthermore, in a scenario where passengers are prevented from boarding the first arriving bus and face a queue to board them, many might walk to nearby stops searching for alternatives, and queues might spill over their area of influence.

Thus, although the simulation indicates crowdedness at the individual vehicle and stop level, we provided an aggregated view of the system. 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 m radius each. We used the hexagonal grid since the nearest neighbor is simpler and more symmetric than rectangular grids, and it has advantages for visualization (Birch et al., 2007). We used 1000 m as an ideal way to represent the 15-minute neighborhood scale in cities and access to bus stops from the hexagon's centroid. Origins and destinations are generated at a transportation-planning zone level, which aligns with the decision to analyze the results using this grid. However, it is important to highlight that the simulation itself does

Table 2
Scenarios tested in our public transport simulation.

Scenario	Public transport demand	Travel Demand Management (TDM)	Capacity	Frequency
1	No change	No	100%	Baseline
2	No change	No	60%	Baseline
3	No change	No	60%	Baseline + 20%
4	No change	No	30%	Baseline
5	No change	No	30%	Baseline + 20%
6	Lockdown	No	100%	Baseline
7	Lockdown	No	60%	Baseline
8	Lockdown	No	60%	Baseline + 20%
9	Lockdown	No	30%	Baseline
10	Lockdown	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	No change	Yes	100%	Baseline
17	No change	Yes	60%	Baseline
18	No change	Yes	60%	Baseline + 20%
19	No change	Yes	30%	Baseline
20	No change	Yes	30%	Baseline + 20%
21	Lockdown	Yes	100%	Baseline
22	Lockdown	Yes	60%	Baseline
23	Lockdown	Yes	60%	Baseline + 20%
24	Lockdown	Yes	30%	Baseline
25	Lockdown	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%

not consider the possibility of walking to a different stop if the selected one is crowded, as decisions are made exogenously from the experienced level of service. In each cell, we provide performance indicators as the aggregate number of people waiting or waiting time percentiles yielded by the simulation of each scenario. Fig. 4 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 by aggregating people waiting at each bus stop 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.

To also analyze metrics visually at a link level, our work also considers a novel visualization tool for the number of passengers 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 Fig. 5a), we calculate the average number of passengers in a virtual arc which only considers those services passing through A and B (in that specific direction) and accounts for 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. For visualization purposes, we considered two scenarios: north and east direction (red arrows in Fig. 5b) and southwest direction (blue arrows in Fig. 5b). The reason for doing so responds to the main direction of the morning peak flows in Santiago, as we detailed in Section 4.2.

4. Results

4.1. Simulation results

Table 3 summarizes 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). We first report the results in terms of waiting times and passenger density impacts for scenarios where TDM is not implemented. We see that, overall, telecommuting significantly improves the level of service experienced by passengers mostly because of fewer people traveling. However, 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 vehicle's capacity has a non-significant effect on the density over 1 pax/m^2 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.

Regarding TDM impacts, we see how travel demand management improves the level of service experienced by passengers. We see that in terms of waiting times for the pandemic demand scenario, travel demand management has a limited 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 % and it is only significant when capacity is limited to 30 %.

Optimum results in terms of reduced passenger density are obtained when limiting transportation capacity to 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 throughout 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 3 min 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.

4.2. Visualization of key scenarios

We visualize the output of the baseline simulation to test if the results represent the aggregate travel patterns and public transport level of service for the 7:30–8:30 am time period. Following Fig. 5 representation, Fig. 6 (top) represents the 80th percentile of passengers traveling in services running in the North and East direction (left figure) and in the South and West direction (right figure). Each line represents a virtual arc between two hexagons. Greener colors show few people traveling, and redder colors show more people traveling. The thicker the line, the higher the aggregated frequency of services between the two hexagons. This form of visualization allows for identifying which areas of the city should be prioritized in a pandemic context that reconfigures the demand levels across the city. It also provides opportunities to adjust frequencies and vehicle capacities to satisfactorily address social distancing in public transport and at the stops.

The comparison in Fig. 6 clearly shows that the most crowded situation in terms of passenger density during the morning peak happens traveling towards the city's northeast, corresponding with the highest number of people waiting at each bus stop (Fig. 6, bottom). This

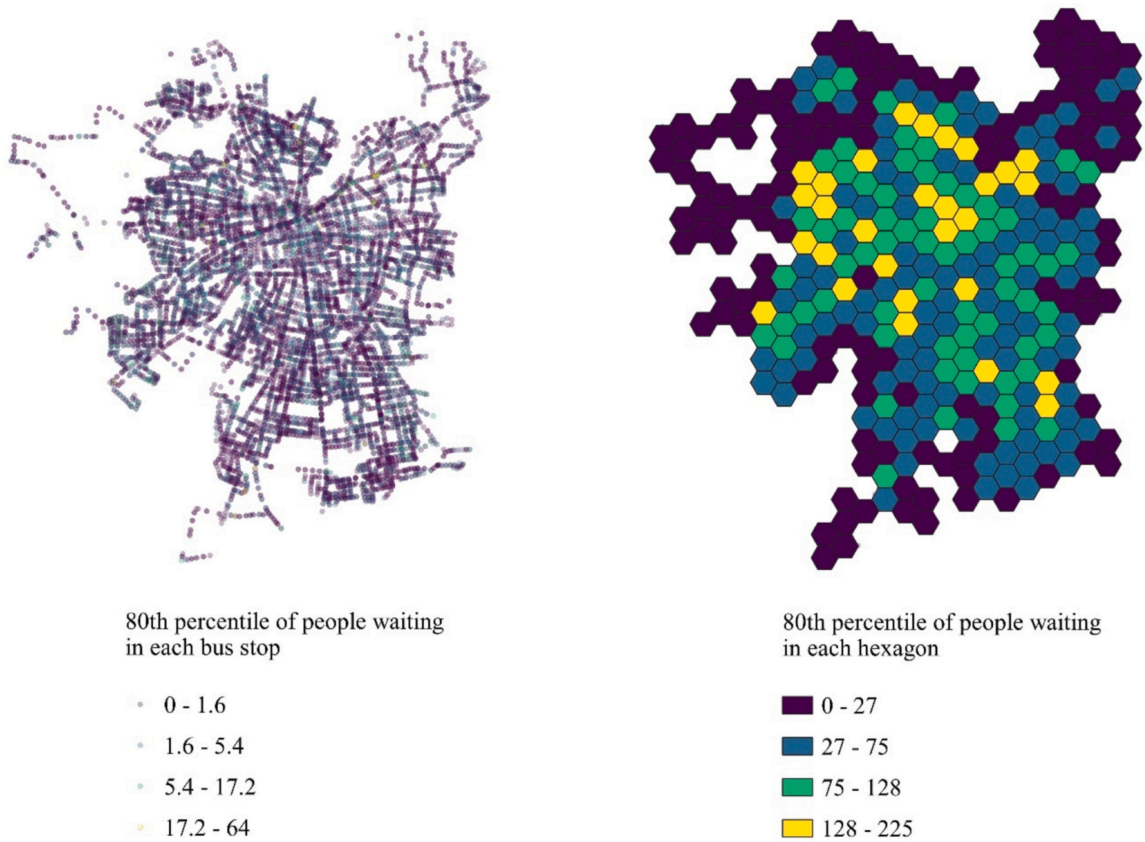

Fig. 4. 80th percentile of people waiting in a) each bus stop b) each hexagon (Source: Own elaboration). Note: This visualization allows us to see how many people are waiting in a given zone. This was the primary concern during the pandemic, where the aim was to avoid overcrowding. This visualization does not allow us to distinguish the waiting time of each individual, which is analyzed in Table 3

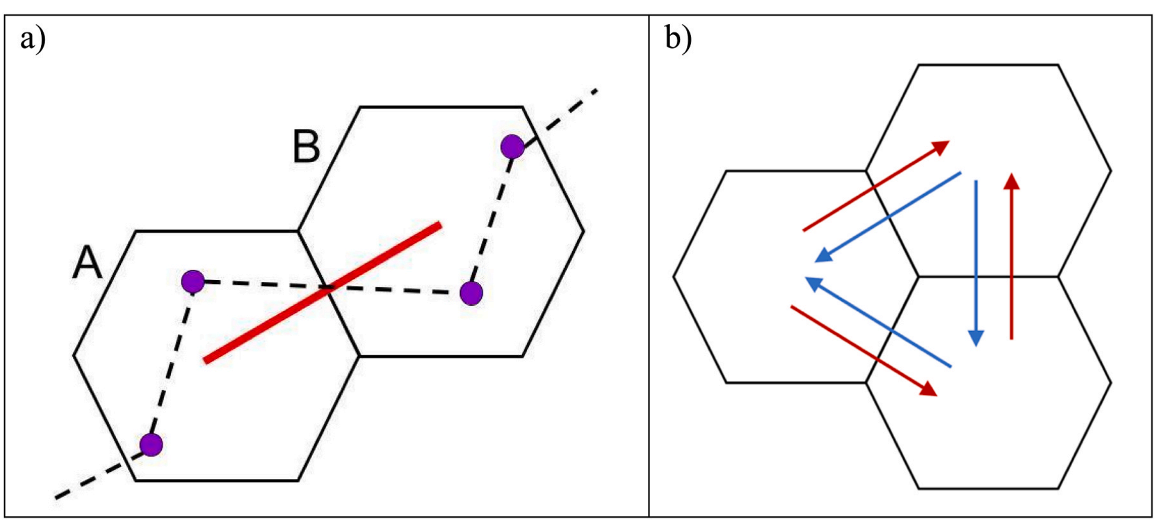

Fig. 5. a) Average number of passengers between two hexagons calculation process. b) Six possible connection directions between consecutive hexagons.

situation reflects the actual activities' distribution in the city, as it is in this area where the most affluent households are located and where the concentration of job opportunities is the highest. The south and west-bound direction are not highly loaded except within the city center and towards this area from the east. Although not analyzed here, this scenario is overall reversed when analyzing the afternoon peak period.

In terms of the visualization results, we decided to focus the analysis on three pairs of scenarios based on the results presented in the previous section. Regarding the number of people travelling inside each vehicle, we opt to focus exclusively on the most loaded direction (Northeast). First, we describe the situation under the pandemic and transition scenarios when capacity is reduced to 60 %, as shown in Figs. 7 and 8. As the demand is lower in the pandemic scenario, we observe that capacity reduction has a limited effect as most links remain green. This situation changes when demand increases in the transition period but to reduced levels compared to the baseline. However, those passenger density levels

Table 3
Simulation results and transportation demand management impact.

		Total waiting time (minutes)			% Pax density over 1 pax/m^2			% Pax density over 3 pax/m^2		
Supply	Demand	No TDM	With TDM	Change	No TDM	With TDM	Change	No TDM	With TDM	Change
Baseline	No change	20.9	19.9	-5%	56%	56%	1%	25%	23%	-9%
	Lockdown	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	No change	39.2	36.3	-7%	54%	54%	0%	14%	12%	-8%
	Lockdown	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	No change	33.5	30.3	-10%	50%	50%	-1%	10%	9%	-13%
+ 20% Freq	Lockdown	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	No change	52.8	50.1	-5%	26%	25%	-2%	0%	0%	-
	Lockdown	44.3	32.3	-27%	17%	12%	-25%	0%	0%	-
	Transition	49.3	43.8	-11%	23%	22%	-5%	0%	0%	-
30% Cap	No change	48.0	45.7	-5%	24%	24%	-1%	0%	0%	-
+ 20% Freq	Lockdown	30.0	23.1	-23%	12%	7%	-43%	0%	0%	-
	Transition	45.3	39.7	-12%	22%	20%	-8%	0%	0%	-

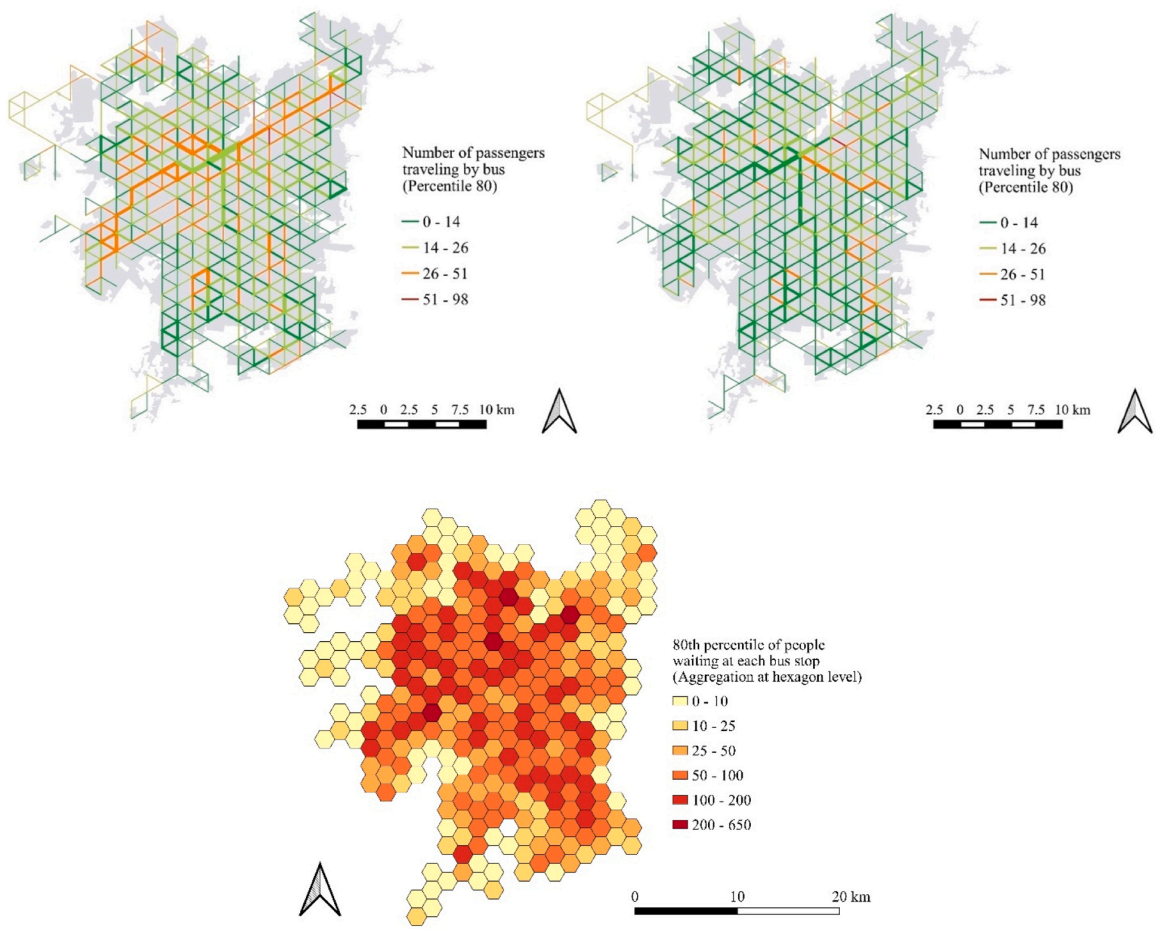

Fig. 6. At the top, 80th percentile of the number of passengers traveling by bus (Left: North and East direction. Right: South and West direction). At the bottom, 80th percentile of the number of people waiting at each bus stop.

won't be acceptable if a social distancing measure is implemented. In terms of the number of people waiting at stops, we observe a critical situation in both scenarios, as the capacity reduction keeps passengers out in order to keep passenger density levels below the specified maximum.

Second, we look at how the situation changes when incorporating TDM into the equation for the pandemic scenario, as shown in Figs. 9 and 10. This scenario is clearly an improvement, especially in terms of the number of people waiting outside. As the number of critical zones gets reduced, it would be easier to focus more on those identified areas. In this particular scenario, reducing capacity to 30 % but increasing the frequency offered has a very limited effect. This is mostly explained because of the reduced transportation demand under this pandemic scenario.

Lastly, we make the same analysis for the same supply scenarios but when the demand increases to transition levels, as shown in Figs. 11 and

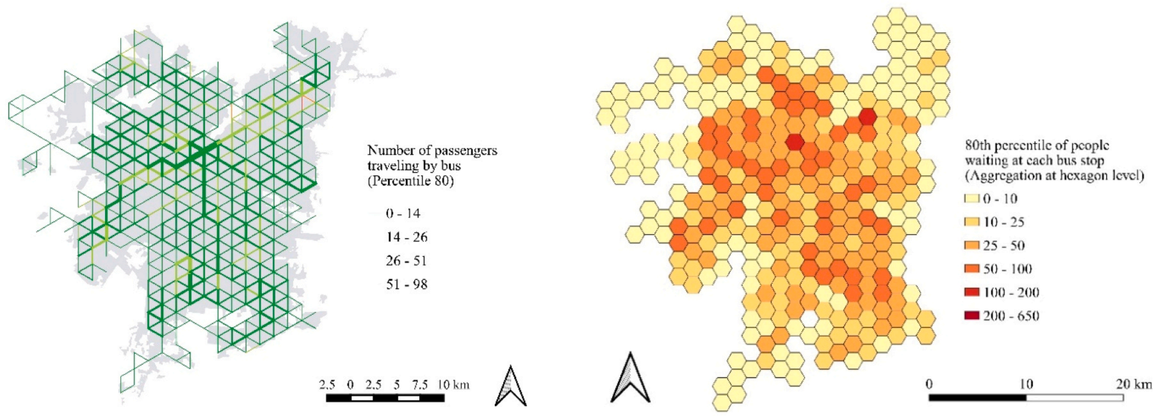

Fig. 7. Scenario 7 Pandemic scenario, supply at 60%.

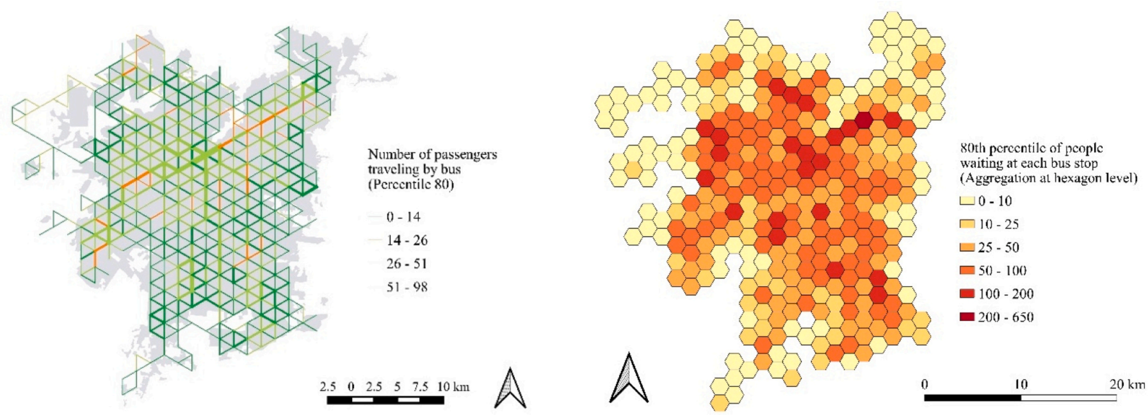

Fig. 8. Scenario 12 Transition scenario, supply at 60 %.

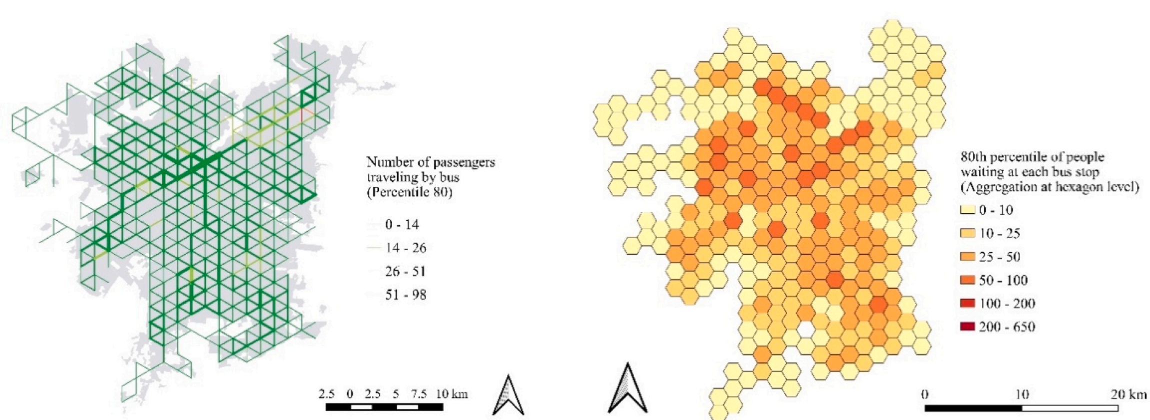

Fig. 9. Scenario 22 Pandemic scenario plus TDM, supply at 60 %.

12. As the demand is higher than in the previous figures, we can see how now there are critical areas in terms of the number of passengers inside each vehicle. Interestingly, TDM keeps almost all links at acceptable levels. Under these conditions, reducing the capacity to 30 % at an increased frequency solves the passenger density issues inside vehicles, but at the cost of increasing the number of critical areas in terms of people waiting to be able to board a bus. Thus, we conclude that TDM, in addition to more specific strategies, such as applying different TDM schedules for the most critical areas might be a better option to face these transportation challenges.

5. Discussion and conclusions

Our work develops a public transport system operation simulation tool to evaluate the impacts of different intervention scenarios in a pandemic context. In particular, we focus on predicting critical locations in the network regarding the level of service experience by the passengers of the entire system. This dissatisfaction could potentially lead to other hazards when considering, for example, that crowding can have an effect on health risks, as during the past pandemic. We made a proof of concept of such a tool by estimating queues lengths of people waiting at

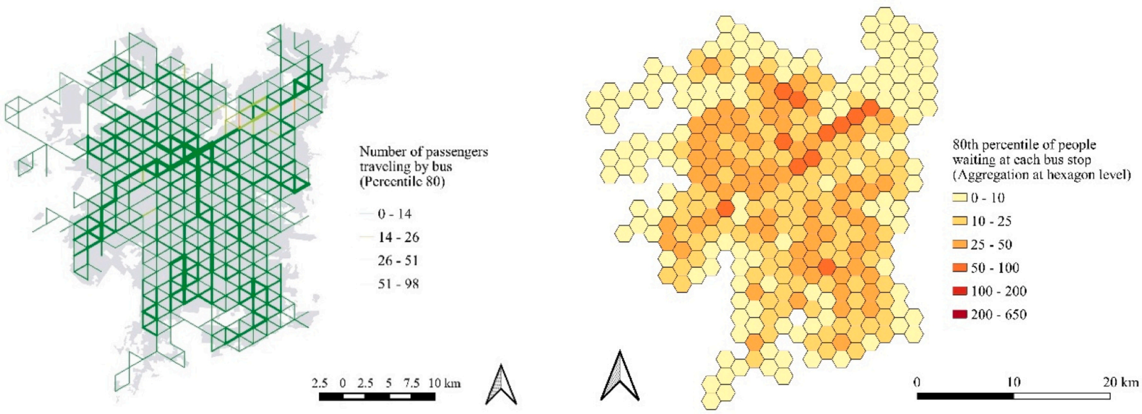

Fig. 10. Scenario 25 Pandemic scenario plus TDM, supply at 30 % and 20 % increase in frequency.

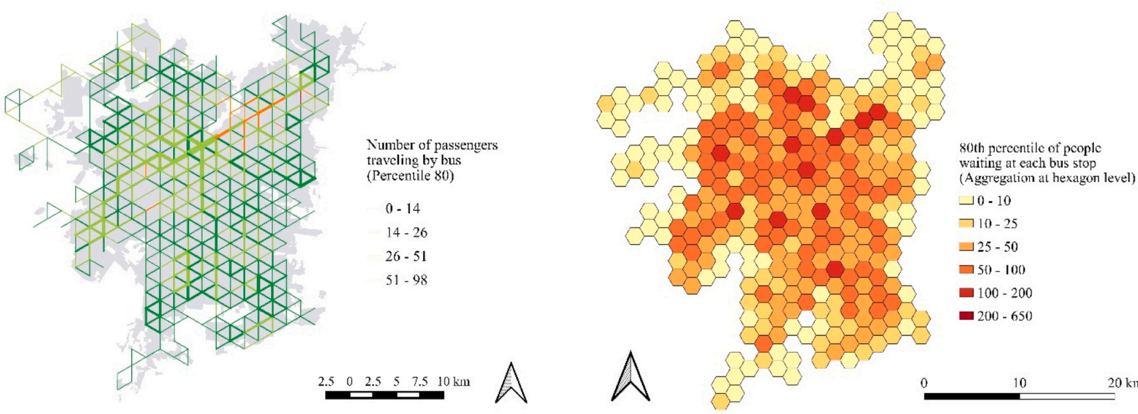

Fig. 11. Scenario 27 Transition scenario plus TDM, supply at 60 %.

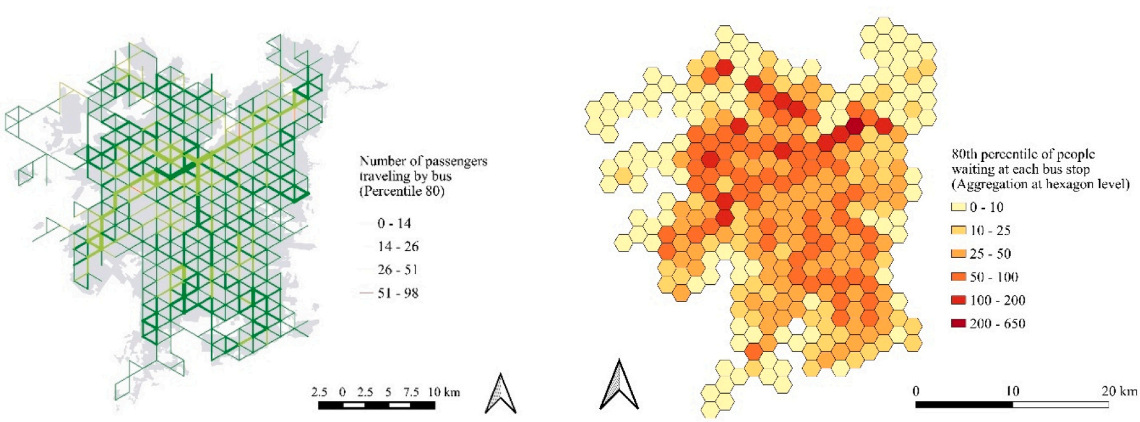

Fig. 12. Scenario 30 Transition scenario plus TDM, supply at 30 % and 20 % increase in frequency.

different stops and passenger 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.

This methodology might be useful beyond the COVID-19 pandemic, visualizing the impact of other types of disruptions that might severely affect the system, such as a massive driver strike that reduces the frequency that can be provided or an unexpected failure affecting a key metro line. Notice that a failure affecting a single car or station might prevent a large stretch of the line from operating. As noted by Cats and Jenelius (2015), disruptions in public transport networks have both direct effect on those links or nodes affected but also the dynamic nature of the supply affects services availability and capacity downstream. In addition, people's choices under these circumstances tend to stick to their habitual decision. Considering they will behave without accounting for their past experience might overestimate the effect of any management strategy implemented (Thorhauge et al., 2020). In particular, we conclude that travel demand management seems to be the better solution as it reduces queues lengths and passenger density to levels which can only be obtained by drastically increasing the frequency offered. However, we take TDM for granted in our simulations, which means that the strategies to deploy it and enforce it are out of the scope of our research. By using hexagons as a form of aggregated and quick visualization, interventions can be focused into a set of desirable stops or routes, which can also help better coordinate with local authorities for proper operation.

In order to generate the hexagonal grid visualization and evaluate different intervention scenarios, the tool must make assumptions about factors such as the number of people traveling by public transport or the willingness to stick to the preferred route and sequence of stops. These assumptions may not always accurately reflect real-world conditions, which could affect the reliability of the tool's results. More importantly, the simulation assumes evenly distributed headways based on the operational plans. However, under disrupted scenarios, this assumption will not hold, and thus the effects on passenger density are underestimated (Soza-Parra et al., 2019), which is critical when aiming to keep social distancing. There may be other factors that impact the operation of a public transport system during a pandemic or other disruptions that are not considered by the tool. For example, the tool may not take into account the availability of alternative modes of transportation or the impact of external events, such as weather, on travel patterns.

Our simulation approach considers a rigid origin-destination matrix, which does not vary if people experience long waiting times or crowding conditions. Although this could be considered a limitation, our case study focuses on the morning peak, where most passengers do not have the option of not traveling to their jobs or places of study. In addition, for a significant portion of the population in Santiago, public transport is the only option for long-distance travel, given that 60 % of households in Santiago do not own a car (SECTRA, 2015).

Our article is well situated in relation to other research conducted during the pandemic For instance, Gkiotsalitis and Cats (2021) conducted a literature review on the adaptations of public transport during the COVID-19 outbreak. They identified various factors that should be considered at different levels, including changes in demand, social distancing measures, and strategic, tactical, and operational planning. An important point they emphasized is the need for planning at all levels to align with national social distancing regulations and to consider relevant variables, such as the probability of disease transmission. In this context, our model also complies with these recommendations by providing metrics for various levels of social distancing and identifying critical areas within the city and services that could increase the risk of infection. Furthermore, there is limited literature on the subject of travel demand management during the pandemic. One example addresses various alternatives for managing demand but lacks a quantitative exploration of the potential effects of each measure (Hörcher et al., 2022). They do, however, conclude that the most likely scenario would involve implementing multiple strategies simultaneously, as each strategy comes with its own set of limitations. Lastly, a recent study discovered a direct relationship between social distancing, measured in terms of passenger density, and the percentage of people wearing face masks concerning crowding aversion (Basnak et al., 2022). This implies that passenger preferences and behaviors are influenced by the level of service provided, which our analysis does not currently account for. This finding suggests the need for further research to investigate this effect in a more dynamic manner.

The tool primarily focused on simulating and evaluating the impacts of different intervention scenarios on the operation of public transport systems (such as buses, trains, or subways). The financial impact of the scenarios investigated is beyond the scope of this research. Future research may focus on how governments can prioritize investments and change in operations considering budget restrictions, particularly during disruptive scenarios such as a pandemic. Additionally, further research can allow different frequency adjustments for every single line, analyzing to what extent a frequency redistribution may lower the costs or how increasing frequency may balance costs incurred for reduced capacity. Also, while the tool may consider the effects of disruptions on car users to some extent, it may not specifically model or analyze the behavior of car users in detail. It is worth noting that the operation of a public transport system can have both direct and indirect impacts on car usage. For example, if a public transport system is disrupted or experiences reduced capacity, some people may switch to using their own vehicles instead. This could have implications for traffic congestion, air pollution, and other factors which are beyond the scope of this research.

While our simulation tool offers valuable insights into the operation of public transport systems during disruptions, it is important to acknowledge its limitations and potential directions for future research. The reliance on assumptions, like even headway distribution and fixed origin-destination matrices, may not fully capture real-world conditions during crises. Future studies should explore more dynamic modeling, encompassing various time periods and more sensitive demand, as for example in a dynamic activity-based model. It would also be valuable to explore the financial impact of the intervention scenarios investigated in this study. This would involve considering budget restrictions and how governments can prioritize investments and operational changes during disruptive scenarios like a pandemic. Additionally, understanding the complex interaction between public transport and private car usage during disruptions and addressing social and equity aspects of these events is crucial for comprehensive transportation planning.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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