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An estimation of the effects of social distancing measures on transit vehicle capacity and operations

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Abstract

The COVID-19 pandemic has a direct impact on public transport operations. In this paper, impacts on transit operations of the physical distancing measures deployed to slow the spread of the virus are analyzed and recommendations are provided. At first, two social distancing optimization solutions are provided in order to keep riders at a safe distance. The first is a discrete optimization that can be used in buses with fixed seats, while the second is a continuous optimization that can be used to distribute riders on a grid and be applied on a bus or subway platform. Assuming that the ridership will eventually go back to its level before the pandemic, the second objective of this research is to address the transit operation parameters that need to be changed in order to serve the pre-COVID ridership level, while respecting the social distancing measures. An O-D distribution has been developed in this paper for New York City (NYC) subway line 1, based on the 2018 NYC Travel Survey conducted by the Metropolitan Transportation Authority. Five scenarios of physical distancing are simulated and analyzed in this paper: 3ft, 4ft, 5ft, 5.4ft, and 6ft of separation between passengers. The results show the number of additional trains required to accommodate the hypothetical pre-COVID ridership. The first is a discrete optimization that can be used in buses with fixed seats, while the second is a continuous optimization that can be applied on a bus or subway platform. The results show that by decreasing the minimum distance from 6ft to 5.4ft, the number of additional trains required to serve the transit demand drastically decreases and hence more resources are saved.

1. Introduction

Since the outbreak of the COVID-19 virus in December 2019, and its official recognition as a global pandemic on March 11, 2020 by the World Health Organization (WHO 2020), the world has plunged into a deep depression that has affected many sectors of activities including transportation. In order to reduce the spread of the disease, governments have initiated travel restrictions and stay-at-home orders for non-essential workers, which in turn impacted transit ridership. All transportation modes have been affected: airlines, bus, railways, and subway systems have experienced an unprecedented free-fall decline in customers. The six feet social distancing recommendation by governments will have an impact on culture and lifestyle all over the world. Even after the end of the sanitary crisis with the stay-at-home order lifted, the social distancing policies may not quickly vanish, as those inveterate habits are likely to become a culture. Since the beginning of the Coronavirus crisis, many studies have been carried out in order to investigate the cause, symptoms, spread and treatments of the COVID-19 virus (Shen et al., 2020; Wei et al., 2020), and also the effect of COVID-19 on traffic accidents (Du et al., 2020; Saladié et al., 2020) and most recently the comprehensive review of social distancing measures implemented by transit operators in the United States (U.S.) and Canada to reduce the spread of the COVID-19 virus (Kamga and Eickemeyer 2021). This paper aims to analyze the operational impacts of the social distancing on transit if the measures enacted by governments are kept beyond the pandemic. Regarding the economic impact of the COVID-19, Thunström et al. made use of epidemiological and economic forecasting to perform a rapid benefit–cost analysis of controlling the COVID-19 outbreak. They examined the net benefits of social distancing to slow the spread of COVID-19 in the U.S., and found that social distancing saves lives, but imposes large costs on society due to reduced economic activities (Thunström et al., 2020). Recently, Gkiotsalitis and Cats made use of a mixed-integer quadratic programming model for the redesign of public transport services, and analyzed the effects of different social distancing policies. (Gkiotsalitis and Cats 2021). Before Gkiotsalitis and Cats' paper, prior studies on social distancing in transportation did not discuss the direct impact of social distancing on public transit operations. Gkiotsalitis

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and Cats designed an objective function that consists of the hourly pas-
senger demand between origin and destination stations, the train fre-
cquency/headway, and the number of trains. They split the hourly
passenger demand in two parts: passengers that can be served and pas-
senger that cannot be accommodated due to social distancing mea-
sures, and are hence denied service. Theretofore, the authors
minimized the objective function in terms of those parameters. Solving
the proposed optimization problem has a good merit in terms of for-
mulation that can then be computed using optimization software pack-
ages. Their optimization algorithm takes as input the expected hourly
passenger arrival rate from an origin station to a destination station,
which is known for the Washington Metropolitan Area Transit Author-
ity (WMATA) studied in their research. However, in this paper, the
transit origin–destination matrix is not available for the New York City
Transit (NYCT), and has to either be estimated or heuristically in-
ferred. Unlike the WMATA system which is an entry-exit system, the
NYCT Subway is not a distance-based fare payment system. NYCT
is the largest rapid transit system in the world by number of stations,
with 472 stations serving 27 subway lines (MTA., 2020a). It carries
millions of passengers daily and operates 24 h a day, 7 days a week.
Yet, there is no system to record the Origin-Destination (O-D) matrix
of passengers, since alighting information is not recorded at the exit
station. In fact, the passenger swipes the fare card (MetroCard) only
at the entry station and not when exiting the system.

In the past two decades, many studies have been done to estimate
stops level transit origin–destination using Automatic Data Collection
(ADC) system (Barry et al., 2002; Trépanier et al., 2007; Li et al.,
2011; Nassir et al., 2011; Wang et al., 2011; Munizaga and Palma,
2012; Aşgär et al., 2016; Kumar et al., 2019; Jafari Kang et al.,
2021; Etikak et al., 2021; Wu et al., 2021). The majority of these stud-
ies used smart card data to estimate O-D for the bus system. Barry et al.
described a methodology to estimate the transit O-D trip tables by
using the New York City Transit’s MetroCard that records the serial
number of the MetroCard and the time and location (subway turnstile
or bus number) of each use. Unfortunately, the developed methodol-
ogy is not revealed in the published paper and the O-D trip tables
for the subway lines are not provided (Barry et al., 2002).

In this paper, the authors developed a methodology to estimate the
stops level O-D trip tables for the Subway Line 1 using the data from
the Metropolitan Transportation Authority (MTA) New York City Tra-
vell Survey (MTA., 2020b). This travel survey performed in 2018,
describes the travel behavior of New York City (NYC) residents from
every borough, irrespective of travel mode and was conducted to pro-
vide data to recalibrate the MTA’s Regional Transit Forecasting Model.
This comprehensive travel data completed the travel diary of at least
one day of 14,416 households, includes 134,903 unweighted trips,
and at least 27,700 linked transit trips throughout New York City. This
survey collected enough information to allow an analysis of origin–desti-
nation patterns on New York City Transit Authority sub-
ways and buses. For the Subway Line 1, there are approximately
3,000 trips providing both the boarding and alighting stations in the
survey. Based on this data, the O-D trip tables at the station
level for Line 1 was estimated.

The initial annual average ridership is distributed along the sta-
tions, based on the estimated O-D trip tables along the subway line.
The ridership data before COVID-19 are the 2018 entry data collected
from the turnstiles at the entrance of the subway stations and publicly
available. The raw data of the entrance turnstiles are aggregated in a
four-hour interval. Given the large size of the dataset, a data ware-
house was constructed in order to deploy an Online Analytical Pro-
cessing (OLAP) cube that consists of 4 dimensions: 1) the Subunit Channel
Position (SPC) that represents the specific location of a turnstile
device, 2) the transaction date, 3) the transaction time, and 4) the sta-
tion, subway line name, and a measure called “entries”, which is the
cumulative entries, i.e., the number of MetroCard swipes registered
for a given SPC.

Given that ridership data at the stop level is available only for the
subway system and not for the bus system in NYC, the research will
use two separate case studies to apply the developed models. There-
fore, the paper is divided in two main sections. In the first section,
the Low Floor Series (LFS) Artic bus and the Xcelsior XD60 bus, are
used as a case study for the bus system. In the second part, the NYC
Subway Line 1 network is taken as the case study for the subway sys-
tem. The additional required number of trains necessary to serve the
pre-pandemic demand level without excessive waiting time is pro-
vided, at every station along Line 1, and for various physical distancing
scenarios.

2. Social distance optimization for seats assignment in the bus

In this section, a seating distribution plan is provided based on a
discrete optimization. The distribution scheme is such that, when pos-
tible, two passengers should not occupy subsequent seats to create a
separation. Since the position of the seats are fixed, it is not possible
to change the distance between seats. Consequently, the only option
to maintain social distancing is to distribute the passengers such that
they do not occupy adjacent seats. The Metropolitan Transportation
Authority (MTA) Regional Bus Operations bus fleet comprises over
5,700 buses, coming from different manufacturers, such as Nova
Bus, DaimlerChrysler North America, Motor Coach Industries, New
Flyer, Prevost, etc. All buses are 102 in. (2.59 m) wide, and fully com-
pliant with the Americans with Disabilities Act of 1990. As shown in
Fig. 1, configurations for most of these bus models consist of double
seats on each side, separated by an aisle. The driver’s seat is isolated
and the back row usually has more seats than others. The bus in
Fig. 1 consists of 45 passengers’ seats plus a driver seat. In order to
maximize the occupancy while maintaining a required distance of sep-
eration between people in the bus, the following strategy is suggested:
1) no standees passenger, 2) the aisle seats should be empty, and 3)
only one passenger should be in the square of four seats. The objective
of the discrete optimization problem is to maximize the number of
people that can stay in a station hall, at a bus stop or the number of
people that can board a vehicle, while meeting the required minimum
separation for physical distance.

Let \( P_i \) be a binary number between 0 and 1, representing the seat
occupancy. \( P_i = 0 \) if the seat is not occupied, and when the seat is
occupied. The objective function is given as:

\[
J = \text{Max} \sum P_i \tag{1}
\]

Subjected to the following constraints

\[
P_i = \begin{cases} 
1, & \text{if occupied} \\
0, & \text{if not occupied} 
\end{cases} \quad i = 1 - 45 
\tag{2}
\]

\[
P_{a_{i}} = 0 \tag{3}
\]

\[
P_{a_{i}} + P_{a_{i+4}} = 1
\]

Where \( P_{a_{i}} \) represents the occupancy of the seats on the aisle. The
optimization process yields the distribution of seats shown in Fig. 1.
The green seats are occupied, while the aisle and the buffer seats are
empty. Only 13 out of the 45 passenger seats are occupied, which
yields an occupancy ratio of 28.89%; we define this ratio as the COVID
bus capacity percentage, \( P_{cov} \). This means that, in order to comply with
the physical distancing measures, only 28.89% of the bus capacity is
actually occupied. Therefore, the bus runs with 71.11% of unused
seated capacity, leaving extra riders at bus stops. In order to serve
these additional riders, the operator can: 1) prioritize articulated bus
over regular buses, 2) enable all-door boarding and alighting, or 3)
increase bus frequency.

Some of the articulated bus in the current NYC bus fleets include:
The LFS Artic with a length of 62 ft (18.9 m), width of 8.5ft (2.59 m),
and a bus loading capacity of 113 persons (62 seats, 50 standees, and

2
The Xcelsior XD60 bus has a length of 60 ft (18.29 m), width of 8.5 ft (2.59 m), and a bus loading capacity of 123 persons (49 seats, 73 standees, and one driver). In a strict case, where no standees should be allowed onboard, the actual bus capacity is as follows: \( N_{Lbus} = 62 \) passengers, \( N_{Wbus} = 49 \) passengers for the LFS Artic, and \( N_{Wbus} = 49 \) passengers for the Xcelsior XD60. This means that, due to physical distancing measures put in place to reduce the spread of the COVID-19 virus, the LFS Artic only serves 18 passengers out of the 112 that could normally be served at normal condition, including standees. Therefore, additional vehicles are needed in order to serve the remaining 94 passengers who couldn’t board the bus at full capacity. In order to serve 94 passengers while observing the social distancing policy, 94 \( P_{cov} \approx 18 \) passengers while observing the social distancing policy, 84 passengers while observing the social distancing policy, 94/18≈5 additional buses are required. The formulation of this problem is generalized as follows:

Let \( C_1 \) and \( C_2 \) be respectively the bus seat capacity, and the bus capacity including the standees, before COVID, and \( C_1 \) the bus capacity after COVID. \( B_{add} \) the additional number of buses required to transport the extra people because of the social distancing policy.

\[
\begin{align*}
C_1 &= \frac{28.89}{C_2} \\
B_{add} &= \left(\frac{C_2}{C_1}\right) - 1
\end{align*}
\]

In the case that standees are allowed in the aisle, the number of additional people that can be served is calculated as:

\[
N_{aisle} = \text{Int}\left(\frac{W_{bus}}{d_{min}}\right); \quad N_{aisle} = \text{Int}\left(\frac{L_{bus}}{d_{min}}\right)
\]

Where the function \( \text{Int}(x) \) represents the integer part of \( x \). \( d_{min} \) is the minimum distance to observe due to the social distancing requirement, \( L_{bus} \) is the length of the bus, \( W_{bus} \) is the width of the bus, \( N_{aisle} \) is the number of people that can fit along the width of the bus, \( N_{aisle} \) is the number of people that can fit along the length of the bus. The total number of people that can fit in the bus is given as

\[
N_{bus} = N_{aisle} \times N_{aisle}
\]

For the LFS Artic bus model, the length is 62 ft (18.9 m), width is 8.5 ft (2.59 m), which has a bus loading capacity of 112: 62 seats and 50 standees. Its buffer length of 3.5 ft and buffer width of 2 ft were removed from the actual dimensions of the bus, to account for the non-passenger area. The actual passenger's area is hence \( L = 58.5 \text{ ft} \) and \( W = 6.6 \text{ ft} \). Table 1 shows the additional standees of the bus as a function of the minimum physical distance. If the minimum physical distance is for example 3 ft, 40 people can stand in the bus, which is still feasible since the standing capacity of the LFS Artic is 50 standees. If we strictly want to respect the 6 ft physical distance recommenda-

| \( d_{min} \) (in ft) | 3 | 3.4 | 4 | 4.4 | 5 | 5.4 | 6 | 6.2 | 6.4 | 7 | 7.4 | 8 |
|----------------------|---|-----|---|-----|---|-----|---|-----|----|---|----|---|
| \( N_{aisle} \) | 20 | 17 | 15 | 12 | 12 | 11 | 10 | 9 | 9 | 9 | 8 | 8 |
| \( N_{aisle} \) | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| \( N_{aisle} \) | 40 | 34 | 30 | 13 | 12 | 11 | 10 | 9 | 9 | 9 | 8 | 8 |
The number of people that can fit into the car or on the platform are given as:

The case study of this paper is the New York City Subway Line 1 shown in Fig. 3. Subway Line 1 train is served by the R62A car model built by Bombardier. The car dimensions are as follows: the length is 51.04ft (15.56 m), the width is 8.60ft (2.62 m), and the height is 11.89ft (3.62 m). Assuming the length of the platform is 10 times the length of a car and the width is 10 feet, we have:

\[ L_{\text{car}} = 51 \text{ ft}; \quad W_{\text{car}} = 8.6 \text{ ft}; \quad L_{\text{plat}} = 510 \text{ ft}; \quad W_{\text{plat}} = 10 \text{ ft}. \]

Line 1 starts at Van Cortlandt Park–242nd Street in the north, travels south to end at the South Ferry station in Lower Manhattan. The maximum number of passengers in subway and platform for different minimum physical distances is shown in Table 2. As the minimum distance \( d_{\text{min}} \) increases, the number of passengers that can fit in the subway car and on the platform decreases. The total number of passengers that can fit on the train and on the platform are given by \( N_{\text{car}} \) and \( N_{\text{plat}} \).

For the 6ft minimum distance requirement, only 8 passengers can fit in a car, or 80 people in a train that has 10 cars. As shown in Table 2, transit operators can considerably increase the number of passengers in a car from 8 to 18, by just relaxing the distance from 6ft to 5.4ft. This would allow additional 100 passengers on a train of 10 cars. On the other hand, the number of passengers on the platform can be increased from 170 to 188, just by relaxing the required distance from 6ft to 5.4ft. For a minimum distance of 3ft, a maximum of 510 people can fit on the platform, while only 170 can fit when the 6ft social distance is required.

4. Methodology

The process of finding the additional number of trains required in order to accommodate the passengers waiting for the next train within the safe social distance is as follows:

1. collect the daily average ridership data entering the subway station at all the stations
2. distribute the ridership northbound and southbound based on the estimated O-D distribution
3. distribute the passengers exiting the train at each station based on the estimated O-D distribution
4. calculate the demand at each station based on the ridership at each station and the alighting passengers
5. distribute the demand hourly based on the temporal travel demand distribution
6. calculate the number of necessary trains by subtracting the pre-COVID hourly demand from the post-COVID platform capacity for a given minimum distance scenario and divide by the number of people that can fit into the train for that given scenario
7. calculate the number of additional trains by subtracting the pre-COVID train frequency from the number of necessary trains calculated in 6.
8. calculate the supply (available space for passengers in the car) based on the capacity for each minimum distance scenario.
9. use the boarding demand and supply to calculate the queue length, i.e. the number of passengers waiting on the platform.

After computing the maximum ridership that can fit in the train and on the station platform, the ideal post-COVID number of trains required to carry all the passengers with no waiting time is given as:

\[ T = \frac{N_0 - N_{\text{plat}}}{N_{\text{train}}} \] (9)

\( N_0 \) is the pre-COVID hourly ridership, \( N_{\text{plat}} \) is the post-COVID maximum number of passengers that can board the train. If \( T \) represents the pre-COVID maximum number of trains, then, the required number of additional trains that is necessary to serve all passengers without waiting time is calculated as

\[ T_{\text{add}} = T - T_0 \] (10)

The New York City Travel Survey data includes approximately 3,000 trips made on the Subway Line 1. By distributing these trips between the boarding and the alighting stations and taking into consideration the transferred passengers to alighting stations not in the Line 1, the estimated station level O-D trip tables is calculated. Table 3 shows an example of O-D trip distribution between the selected stations on the Line 1.

The data used as reference for the pre-COVID ridership is the weekday average ridership data. For stations served by multiple subway lines, the ridership for each line at the station is calculated based on the proportion of the boarding subway line revealed in the travel survey. Fig. 4 displays the estimated average weekday ridership (entrance at turnstiles) for Line 1 and for other lines at all stations of Line 1 based on the proportions calculated from the travel survey data. As an example, the average weekday ridership at the Times SQ-42 ST station is 178,248 in 2018. At the time of the writing of this paper, this station shows an example of O-D ridership, which necessitate less than one full train at V. CORTLAND, and four additional trains at 238 ST, only during AM peak-time. From 231 ST onward, the number of additional trains gradually increases, but mostly only during AM and PM peak-time.

As shown in Fig. 6, the number of additional trains reach its maximum around midtown, about 63 trains at Times Square at 7 AM, and 45 trains at 34 St-Penn Station, during AM peak-time, for the 6ft scenario. Likewise, at PM-peak (4 PM), about 54 additional trains would be required at Times Square, and 37 trains at 34 St-Penn Station, for the 6ft scenario. After these two hub stations, the number of additional trains keeps decreasing as the train moves south, and ends up with no additional required trains at South Ferry Station, which is the southernmost station, as shown in Fig. 6. A summarized view of the additional number of trains required, per station, for each of the 24 h of the day is shown on the heatmap in Fig. 7, for four different scenarios: 6ft, 5.4ft, 4ft, and 3ft. The blue part of the heatmap represents region and time period where less additional trains are required, while the yellow color means higher additional trains are required. On this figure, it can be observed that, for the 6ft and 5.4ft scenarios, more trains are required at hub stations: CATHEDRAL PKWY (ID = 15), to 34 ST-PENN (ID = 25), during AM and PM peak-time. Almost all the area of the heatmap of the 3ft scenario is blue, except for the AM-Peak, around 86 ST (ID = 18), and TIMES SQ-42 ST (ID = 24).

As shown above, the required number of additional trains for the 6ft physical distance recommended by governments around the world is so high and unpractical to implement. The different distance scenarios analyzed here suggest that one can decrease the required distance slightly, and save a lot in terms of required vehicles. One interesting finding is that, by enforcing a 5.4ft minimum distance instead of 6ft, the number of additional trains drastically decreases. Table 4 clearly shows the benefit of reducing the minimum distance requirement. For example, the maximum number of additional trains during the AM peak-hour is respectively: 117.16 for 6ft, 49.19, for 5.4ft, 43.69, for 5ft, 32.26, for 4ft, and 13.50 for 3ft. These maximum numbers are reached at 66 ST-LINCOLN station (ID = 21). The 3ft scenario is more realistic since the maximum number of additional trains needed in this case is only about 13.5 trains, during the AM peak-time, and 5.5 trains during the PM peak-time.

6. Supply and demand for each distancing scenario

In this section, a cumulative supply and boarding demand curve is plotted in order to determine the queue length at each station. The boarding demand at station i, is calculated as:

\[ D_i = R_{i-1} + R_i - E_i \] (11)

Where \( R \) and \( R_{i-1} \) stand for the ridership, i.e. the turnstile entry volume at the current station i, and at the previous station, i-1, respectively. \( E_i \) represents the sum of exits along the line, up to the current station, i.e. the cumulative number of passengers that have alighted the train in all previous stations, up to the current train station i.

The supply at a station i, is calculated as:

\[ S_i = C - Q_i + E_i \] (12)

Where C is the train capacity, and Q is the train occupancy at station i. The daily boarding demand was distributed hourly based on the temporal ridership demand and used as occupancy.
The cumulative boarding demand and supply curve for different social distancing measure policies are shown in Fig. 8 and Fig. 9, for each distance scenario, and for the northernmost, midtown and southernmost stations. As observed in these plots, the demand (blue line) is lower than the supply at the two northernmost stations; it keeps increasing as the trains move southbound, while the cumulative supply decreases. After only 1 station, the cumulative demand starts moving over the cumulative supply for the 6ft distance policy scenario. At midtown, the cumulative demand surpasses the cumulative supply for all the social distance measures, except for the 3ft scenario where the supply is still over the demand in most stations. As we further move southbound, the cumulative supply gradually starts taking over the cumulative demand again, see Fig. 9. In most of the cases, the boarding demand of the 6ft social distancing policy is way above the supply curve, meaning that the number of stranded passengers, i.e. passengers that cannot board the train, would be higher if we were the abide by the 6ft rules. With the 3ft scenario, the supply will be enough to tackle the demand along all the stations of the line.

Table 3

| Boarding Stations (Origin) | Subway Lines | Aligning Stations (Destination) |
|---------------------------|--------------|---------------------------------|
|                           |              | 116th St - Columbia University  |
|                           |              | 96th St St - Lincoln Circle      |
|                           |              | 72nd St - Lincoln Ctr           |
|                           |              | 59th St - Columbus Sq           |
|                           |              | 50th St - Times Sq - 42nd St    |
|                           |              | 34th St - Penn Station          |
|                           |              | 28th St - Christopher Sq        |
|                           |              | South Ferry                     |
| 145th St                  | 1            | 10.77% 6.15% 7.69% 3.08% 6.15% 1.54% 7.69% 7.69% 1.54% 4.62% 1.54% 0.00% |
| 137th St - City College   | 1            | 0.00% 12.05% 2.41% 1.20% 9.64% 4.82% 13.25% 10.84% 0.00% 3.61% 1.20% 0.00% |
| 125th St                  | 1            | 2.04% 8.16% 6.12% 2.04% 6.12% 6.12% 10.20% 2.04% 4.08% 2.04% 0.00% 0.00% |
| 116th St - Columbia University | 1       | 0.00% 7.26% 4.03% 2.42% 7.26% 4.03% 19.35% 4.03% 2.42% 4.03% 1.61% |
| Cathedral Pkwy (110th St) | 1            | 0.00% 4.76% 4.76% 6.35% 12.70% 4.76% 12.70% 1.59% 0.00% 6.35% 0.00% 4.76% |
| 103rd St                  | 1            | 6.83% 12.42% 5.99% 6.83% 6.83% 12.42% 13.04% 6.83% 2.48% 1.86% 0.62% 1.24% |
| 96th St                   | 1, 2, 3      | 7.07% 0.00% 3.03% 6.06% 10.10% 11.11% 11.11% 3.03% 2.02% 2.02% 0.00% 0.00% |
| 86th St                   | 1, 2         | 6.30% 7.87% 4.72% 1.57% 11.81% 7.09% 14.17% 9.45% 0.79% 0.79% 0.79% 0.79% |
| 79th St                   | 1, 2         | 2.00% 5.00% 9.00% 5.00% 15.00% 5.00% 14.00% 8.00% 0.00% 3.00% 0.00% 2.00% |
| 72nd St                   | 1, 2, 3      | 1.82% 6.36% 0.00% 2.73% 16.36% 6.36% 8.18% 7.27% 2.73% 3.64% 1.82% 0.91% |
| 66th St - Lincoln Ctr     | 1, 2         | 0.75% 11.94% 4.48% 0.00% 6.72% 8.21% 17.91% 2.99% 1.49% 2.99% 2.24% 2.99% |
| 59th St - Columbus Circle | 1, A, B, C, D| 1.45% 11.59% 7.97% 0.00% 0.00% 3.62% 20.57% 4.35% 1.45% 0.72% 0.72% 4.35% |
| 50th St                   | 1, 2         | 4.76% 10.48% 5.71% 3.81% 1.90% 0.00% 0.95% 9.52% 2.86% 1.90% 0.95% 6.67% |
| Times Sq - 42nd St        | R, W, S, A, C, E | 4.20% 0.00% 3.36% 6.72% 5.88% 2.52% 0.00% 6.72% 3.36% 1.68% 2.52% 0.84% |

Fig. 4. Estimated average weekday ridership (entrance at turnstiles) for Line 1 and for other lines at all stations of Line 1 based on the proportions calculated from the 2018 NYC travel survey data.

The cumulative boarding demand and supply curve for different social distancing measure policies are shown in Fig. 8 and Fig. 9, for each distance scenario, and for the northernmost, midtown and southernmost stations. As observed in these plots, the demand (blue line) is lower than the supply at the two northernmost stations; it keeps increasing as the trains move southbound, while the cumulative supply decreases. After only 1 station, the cumulative demand starts moving over the cumulative supply for the 6ft distance policy scenario. At midtown, the cumulative demand surpasses the cumulative supply for all the social distance measures, except for the 3ft scenario where the supply is still over the demand in most stations. As we further move southbound, the cumulative supply gradually starts taking over the cumulative demand again, see Fig. 9. In most of the cases, the boarding demand of the 6ft social distancing policy is way above the supply curve, meaning that the number of stranded passengers, i.e. passengers that cannot board the train, would be higher if we were the abide by the 6ft rules. With the 3ft scenario, the supply will be enough to tackle the demand along all the stations of the line.

Fig. 10 shows the cumulative demand and supply curve for the 3ft and 6ft social distancing measures policies, for the two northernmost stations on Line 1. As observed in these plots, the stranded or queuing passengers, i.e., the passengers that could not board the train and waiting on the platform, is the difference between the demand and the supply. The queue actually exists when the demand is greater than the supply, in this case the queue is positive. A negative queue means that the demand is less than the supply. In other words, when the queuing is negative, no stranded passengers is left behind, which is the desired situation; in this case the negative values of the queue are set to zero in the plots.

7. Discussions and recommendations

As the allowed number of passengers onboard reduces, many transit operation parameters should be adjusted in order to meet the ridership demand. Among, those parameters, the dwell time and the train frequency are the most predominant factors that need to be adjusted. In fact, the dwell time directly affects the train headway and the line capacity. The main components of dwell time are: 1) passenger flow time, 2) the door open and close time, 3) time the doors remain open after passenger flow ceases, and 4) the time waiting to depart once the doors close. Of these factors, passenger flow time is usually the main and the most difficult to control. It is not straightforward to know
beforehand whether social distancing will decrease or increase the dwell time at a station. In fact, with the decrease of the number of boarding passengers, the passenger flow will be less congested. There will be less people alighting and boarding, which will shorten the dwell time. However, the minimum distance to observe between passengers waiting on the platform will add up extra time to the boarding time, which in turn may lengthen the dwell time at a station. Ideally, in order to serve more passengers, the post-COVID dwell time at a station should be smaller than the pre-COVID dwell time. Since this may not be feasible, the other options to compensate this longer potential dwell time is: 1) to add additional cars to the train or use articulated buses in order to increase capacity and therefore accommodate more
passengers, 2) off-board or off-station fare payment using mobile apps, 3) all-doors boarding, 4) grade-separated junctions, also called flying junction can also be used in order to avoid the additional waiting time for a train to reach a station, and 5) automatic train operation. Adding additional cars on train will increase the train capacity. Although additional cars on the train can make the train longer than the platform, it

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**Fig. 7.** Number of additional trains needed for different distancing scenarios.

**Table 4**

Number of additional trains needed during AM Peak time, for different distancing scenarios.

| ID | Station          | 7 AM 6ft | 5.4ft | 5ft | 4ft | 3ft |
|----|------------------|----------|-------|-----|-----|-----|
| 0  | V.CORTLANDT PK  | 0.87     | 0.00  | 0.00| 0.00| 0.00|
| 1  | 238 ST           | 4.05     | 0.00  | 0.00| 0.00| 0.00|
| 2  | 231 ST           | 14.26    | 3.46  | 2.53| 0.60| 0.00|
| 3  | MARBLE HILL-225 | 19.88    | 5.96  | 4.78| 2.33| 0.00|
| 4  | 215 ST           | 21.33    | 6.60  | 5.36| 2.78| 0.00|
| 5  | 207 ST           | 26.85    | 9.05  | 7.57| 4.48| 0.00|
| 6  | DYCKMAN ST       | 32.77    | 11.69 | 9.94| 6.30| 0.26|
| 7  | 191 ST           | 39.66    | 14.75 | 12.69| 8.42| 1.34|
| 8  | 181 ST           | 47.32    | 18.15 | 15.76| 10.77| 2.54|
| 9  | 168 ST           | 49.30    | 19.03 | 16.55| 11.39| 2.85|
| 10 | 157 ST           | 55.89    | 21.96 | 19.19| 13.41| 3.88|
| 11 | 145 ST           | 61.64    | 24.52 | 21.49| 15.18| 4.79|
| 12 | 137 ST CITY COL  | 72.30    | 29.25 | 25.75| 18.46| 6.46|
| 13 | 125 ST           | 74.07    | 30.04 | 26.46| 19.01| 6.74|
| 14 | 116 ST-COLUMBIA  | 79.40    | 32.41 | 28.59| 20.65| 7.57|
| 15 | CATHEDRAL PKWY  | 86.41    | 35.53 | 31.40| 22.80| 8.67|
| 16 | 103 ST           | 93.84    | 38.83 | 34.37| 25.09| 9.84|
| 17 | 96 ST            | 105.16   | 43.86 | 38.89| 28.57| 11.61|
| 18 | 86 ST            | 106.75   | 44.57 | 39.53| 29.06| 11.86|
| 19 | 79 ST            | 113.32   | 47.49 | 42.16| 31.08| 12.89|
| 20 | 72 ST            | 112.18   | 46.98 | 41.70| 30.73| 12.72|
| 21 | 66 ST-LINCOLN    | 117.16   | 49.19 | 43.69| 32.26| 13.50|
| 22 | 59 ST COLUMBUS   | 107.66   | 44.97 | 39.89| 29.34| 12.01|
| 23 | 50 ST            | 97.97    | 40.66 | 36.02| 26.36| 10.49|
| 24 | TIMES SQ-42 ST   | 61.88    | 24.62 | 21.58| 15.26| 4.82|
| 25 | 34 ST-PENN STA   | 44.82    | 17.04 | 14.76| 10.01| 2.15|
| 26 | 28 ST            | 38.06    | 14.04 | 12.05| 7.93 | 1.09|
| 27 | 23 ST            | 30.83    | 10.83 | 9.16 | 5.70 | 0.00|
| 28 | 18 ST            | 28.69    | 9.87  | 8.31 | 5.04 | 0.00|
| 29 | 14 ST            | 21.70    | 6.76  | 5.51 | 2.89 | 0.00|
| 30 | CHRISTOPHER ST   | 19.50    | 5.79  | 4.63 | 2.21 | 0.00|
| 31 | HOUSTON ST       | 18.15    | 5.19  | 4.09 | 1.80 | 0.00|
| 32 | CANAL ST         | 15.59    | 4.05  | 3.07 | 1.01 | 0.00|
| 33 | FRANKLIN ST      | 13.46    | 3.10  | 2.21 | 0.36 | 0.00|
| 34 | CHAMBERS ST      | 8.81     | 1.04  | 0.35 | 0.00 | 0.00|
| 35 | WTC-CORTLANDT    | 8.50     | 0.90  | 0.23 | 0.00 | 0.00|
| 36 | RECTOR ST        | 1.52     | 0.00  | 0.00 | 0.00 | 0.00|
| 37 | SOUTH FERRY      | 0.00     | 0.00  | 0.00 | 0.00 | 0.00|
can be used as a critical measure to alleviate the congestion due to the pandemic crisis if the station platform is able to accommodate the additional cars. Automatic train operation allows a train to run at its optimum speed. It also allows the train to brake exactly when it should, at the last possible moment when approaching a station. This reduces not only the station-to-station travel times, but also, it minimizes the critical station close-in time, which is the time from when one train starts to leave a station until the following train is berthed in that station. This can increase total line capacity by 2 to 4% (Transportation Research Board 2017).

As observed by the analyses in this paper, if passengers were observing the standard 6 feet distancing, the number of additional trains necessary to carry all the passengers would be very high, so much that the transit operator may not even be able to cope with the resources required to meet the demand. Practical train operations, measures and policies are suggested below, in order to reduce the spread of the virus while maintaining a reasonable physical distancing on board of vehicles and at stations. These recommendations will help to serve a pre-COVID demand level without jeopardizing passengers health.

7.1. Mask-wearing

As of today, the very first essential protective component measure that comes to mind is the mask-wearing. In many places, transmission of the COVID-19 virus has successfully been decreased with the mask
is very much a feasible approach. Thus, using, for example, 5.4ft or 4ft rather than the WHO recommended 6ft, as minimum distance while passengers wearing masks is very much a feasible approach.

7.2. Increase the number of vehicles and alternate modes

The simplest and most obvious way to transport the passengers without noticeable waiting time is to increase the number of vehicles, especially during peak-time. However, increasing the number of trains is constrained by the available resources and the minimum safe headway that should be met between two consecutive trains. Hence, one cannot indefinitely increase the number of trains in operation. Other policy should supplement the need to increase the number of vehicles as a solution. Alternatively, the transit agency can provide alternate modes, such as buses, between major stations running in parallel with the subway line. This can address the on-time travel needs of essential workers and other passengers.

7.3. Reduce the density of travelers during peak-time

As shown by the analyses in this paper, most of additional train resources to meet the demand while applying physical distance measures are required during peak-hours. A strategy to reduce the density of travelers during morning and afternoon peak will help balance the resources during peak and off-peak hours. Among those strategies, one can list: 1) incentivize off-peak travel, by offering bonus points or discounts fares for travelling off-peak time; 2) penalize trips during peak time by increasing the travel fees during peak-time, and requiring a travel fee for those who normally have a free travelling pass, for example, kids and seniors and people with disabilities; 3) working hour management; in fact, companies should be reorganized into shift work, spreading their employees all along the 24 h, incentivizing workers who prefer working during off-peak time; 4) limiting ticket sales during peak-hours; travel agencies can enact a peak-time ticket quota policy, that will limit the number of ticket sold during peak-hours; and 5) seat reservation; reserving the seat in advance will help riders notice when there are no more seats, and help them take a better decision.

7.4. Other operational measures

The following are additional measures that could be implemented by transit operators to reduce the spread of the virus in the transit system:

Floor and seats stickers: pasting stickers on the floor and in the vehicle will help riders estimate the distance between them and their neighbors. Without the visible stickers, the distance estimation would be relative. Stickers can also be pasted on seats to indicate to the users the forbidden and the allowed seats.

Providing real-time vehicle capacity information: Providing real-time vehicle capacity information will allow the traveler to know which vehicles are less crowded and have available capacity. Developing smartphone applications that inform travelers about the vehicle capacity and suggest them the time slot where they can travel with less risk is suggested.

Off-board fare collection: Off-board fare collection will allow all-door boarding, hence speeding up the boarding process by reducing the dwell time. As stated by the National Association of City Transportation Officials (NACTO), off-board fare collection and all-door boarding cut dwell time substantially, leading to more competitive travel times, greater reliability, and growing ridership (NACTO 2017).

Remove benches in facilities: benches and tables encourage crowding in facilities. Removing them will discourage gathering and decrease the number of travelers waiting in those areas.

Many of the above measures have already been deployed around the world. For example, on March 20, 2020, the New Zealand Ministry of Health recommended that all New Zealand public transportation agencies provide discounts for off-peak travel (Baker et al., 2020). The European Commission made a similar recommendation for railways on May 13, 2020, stating that off-peak hour travel should be encouraged with incentives, such as adjusted pricing, or flexible working hours in the case of commuter trains, to avoid crowding (The European Union 2020). On May 14, 2020, the City government and Transport for London temporarily suspended the Freedom Passes and free travel for individuals under 18 years of age during peak hours, in order to discourage transit travelers (Independant 2020). Danske Statsbaner (DSB), the largest rail provider in Denmark developed a web application that provide the occupancy rate per train, and recom
mendation of departure time in order to minimize the density of travelers and hence, keep social distance (APTA 2020). On May 13, 2020, the European Commission recommended that rail operators remove items in facilities that encourage crowding, such as benches and tables. Many other COVID-19 prevention measures can be found in this reference (The European Union 2020).

8. Conclusion

This paper qualitatively and quantitatively shows the challenges that the transit operators and users will face if the standard 6ft social distancing measure were to be enforced, as the level of ridership bounces back to its level before the COVID pandemic. Given a transit vehicle of usable length L and width W, and the minimum distance requirement, we calculate the maximum number of people that can board into a transit bus. Based on the travel survey conducted in 2018 by the Metropolitan Transportation Authority and the 2018 ridership data collected from the entry turnstiles at stations of the NYC Subway Line 1, we were able to calculate the number of passengers sitting on the subway platform and also board into a train of 10 cars. The results show that in order to meet the 6ft minimum distance requirement, a very large amount of trains is required. For example, about 144 trains is required in one hour, at 66 ST-LINCOLN, during the AM peak-time, which may be infeasible to satisfy. Relaxing the social distance measure policy just by few inches can drastically decrease the number of trains required. Reducing the distance from 6ft to 5.4ft for example brings the maximum number of trains at 66 ST-LINCOLN from 144 to 61 trains, which is about 42% reduction. Since 61 trains is still a very large number of trains to deploy, several other scenarios were analyzed. The 3ft scenario will require a maximum of 18 trains at 66 ST-LINCOLN during AM peak-time. The takeaway of this paper is that, the 3ft social distance requirement along with other measures such as mask-wearing, floor and seats stickers, and off-board fare collection are more practical than the 6ft social distancing policy which is nearly impossible to realize without sacrificing the level of service.

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CRediT authorship contribution statement

Camille Kamga: Conceptualization, Methodology, Supervision, Writing - review & editing. Rodrigue Tchamna: Investigation, Methodology, Data curation, Writing - original draft, Writing - review & editing. Patricio Vicuna: Conceptualization, Data curation. Sandeep Mudigonda: Conceptualization, Methodology, Writing - review & editing. Bahman Moghimi: Conceptualization, Methodology.

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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