INSTITUTO TECNOLÓGICO DE AERONÁUTICA
CURSO DE ENGENHARIA CIVIL-AERONÁUTICA

INTERNSHIP REPORT

New York University

Tandon School of Engineering

New York, NY, October 3rd 2016

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APPROVAL SHEET

Final Curricular Internship Report accepted in 10/03/2016 for the following signers:

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Period
From May 23rd 2016 to July 22nd 2016
Total Hours: 240 hours

I. INTRODUCTION

This report aims to present the work done during my internship, between May 23rd and July 22nd. In order to make more clear what was achieved in this research, attached to this report is a paper, which was submitted for presentation and publication review in the Transportation Research Record journal, that explains exactly what was the purpose of my research, the methodology used and the results obtained.

II. THE COMPANY

II.1. Historic

The NYU Tandon School of Engineering is the oldest private engineering and technology school in the United States. It dates from 1854 when the NYU School of Civil Engineering and Architecture, as well as the Brooklyn Collegiate and Polytechnic Institute, were founded.

The mission of NYU Tandon School of Engineering is to "excel as a leading high-quality research institution engaged in education, discovery, and innovation with social, intellect, and economic impact in the New York region, the nation, and the world".

II.2. Internship Field

The research was developed in the Center for Urban Intelligent Transportation Systems (UrbanITS), a sponsored research center in the Tandon School of Engineering.

II.3. Internship in the Company's Context

The research is part of the annual Summer Research Program for College Students which provide the opportunity to students all over the United States to carry out cutting-edge research in a rapidly growing and technologically important diverse field of engineering interfaces.

III. DEVELOPED ACTIVITIES AND CONCLUSION

The focus of this internship was to make a simulation study to compare autonomous vehicle fleet against Brooklyn-Queens street car line.

Brooklyn-Queens Waterfront Connector (BQX) is a proposed streetcar line, politically backed by Mayor Bill de Blasio, that was announced in 2016 and has a total cost estimated at $2.5 billion. The New York City Development Corporation (NYCEDC) and the New York City Department of Transportation (NYCDOT) conducted an assessment in order to evaluate the BQX Technical Feasibility and Impact Study, completed in 2015 by a non-profit organization called Friends of the BQX. In this assessment document, we have access to, among other information, full origin-destination matrix and average waiting/travel in this system per periods.

As explained before, attached to this report is a paper which explains in the detail all the developed activities and explains the conclusions of this research.

Simulation experiment to compare light rail streetcar against shared autonomous vehicle fleet for Brooklyn Queens Connector

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ABSTRACT

Policymakers predict that autonomous vehicles will have significant market penetration in the next decade or so. One rising market opportunity is the shared autonomous vehicle fleet, which has been shown in several simulation studies to be an effective public transit alternative. In this study, the effectiveness is directly compared to an upcoming transit project proposed in New York City: the Brooklyn-Queens Connector light rail project. An event-based simulation model is developed to compare the performance of the shared autonomous vehicle system against the light rail system under the same demand patterns, route alignment, and operating speeds. The simulation experiments reveal that a shared autonomous vehicle fleet of 500 vehicles of 12-person capacity (consistent with the EZ10 vehicle) is needed to match the 39 vehicle light rail system if operating as a fixed route system. However, as a demand-responsive system, a fleet of only 150 vehicles would lead to the same total travel times (22 minutes) as the 39 vehicle fleet light rail system. Furthermore, a fleet of 450 12-person vehicles in a demand-responsive operation would have the same average wait times and total travel times reduced by 36%. Implications on system resiliency, idle vehicle allocation, and vehicle modularity are discussed.

Keywords: public transit, light rail, shared autonomous vehicles, event-based simulation

1. INTRODUCTION

Autonomous vehicle technologies have matured in recent years to the point that many predict will make some significant market penetration between 2020 and 2030 *[1]*. One particular market is in public transit. Shared autonomous vehicle (SAV) fleets offer the opportunity to replace conventional transit and taxi options, and has seen tremendous interest from traditional auto manufacturers like Ford *[2]* to new startups (e.g. EasyMile, BestMile, NEXT Future Transportation) operating in progressive cities like Dubai *[3]* and Singapore *[4]*, and the first U.S. deployment in Concord, California *[5]*.

This raises the question of how effective SAV fleets can be when compared to traditional transit fleets. A number of simulation studies have been published covering this question. Brownell and Kornhauser *[6]* used simulation to evaluate the fleet size needed for SAVs to serve the whole state of New Jersey, resulting in a fleet of 1.6 to 2.8 million six-passenger vehicles. Fagnant et al. *[7]* compared a city-wide simulation of sample trips made using SAV versus driving to show that SAV can replace nine conventional cars per 24-mi by 12-mi area in Austin. Liang et al. *[8]* examined the use of electric SAVs as a last mile solution and tested it a simulation of arrivals at the Delft Zuid station in The Netherlands, resulting in a fleet requirement of 60 vehicles. *None of the SAV studies have conducted a direct comparison of operations against an existing or proposed transit line*.

We propose to conduct such a comparative study. In New York City (NYC), a new $2.5 billion light rail (LRT) street car line called the Brooklyn-Queens Connector (BQX), was recently proposed by the mayor *[9]*. The alignment of this 17-mile line is shown in Fig. 1. Daily ridership demand is forecast by NYC Economic Development Corporation (NYCEDC) to be 48,900 (15.2 million annual riders) by 2035 *[10]*. The issue is that whereas the streetcar would cost $97.7M per mile, a similar dedicated bus service like the Select Bus Service (SBS) in NYC would operate at the same operating speed of 10.9 mph *[11]* and for only 1.2% of the cost at $1.23M/mi *[12]*. With such a high cost difference and similar performance in such a transit technology investment decision, alternative transit technologies like SAV make sense to be compared. Also, due to its location along the waterfront, operating an SAV fleet could be possible with minimal interference with passenger traffic. The two technologies are shown side by side in Fig. 2.

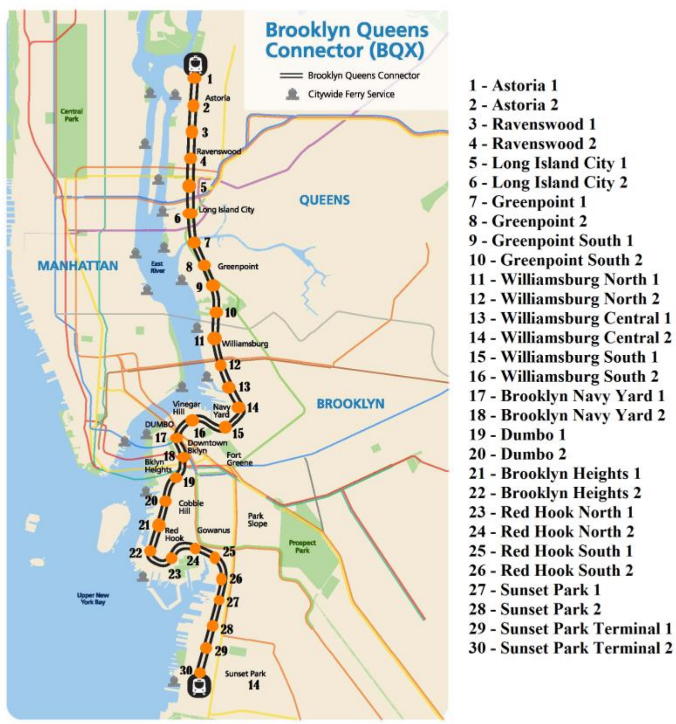


Fig. 1. Proposed BQX alignment (source: NYCEDC *[13]*) with 30 assumed stops superimposed.

(a) (b)

Fig. 2. Comparison of (a) SAV fleet technology (source: EasyMile *[5]*), and (b) NYC-proposed BQX streetcar system (source: NYCEDC *[13]*).

In our study, we pose the following research question: if the BQX was to be completely replaced by an SAV fleet, what fleet size and operating policy would be needed to serve the same forecasted ridership demand under the same performance levels (wait time, travel time).

This question can be answered using a straightforward event-based simulation experiment. In the proposed BQX, a fleet of 39 vehicles with 150 person capacity are used to serve the projected ridership. If SAV fleets using 12 people capacities (such as the EZ10 vehicles from EasyMile) were used instead, a basic conversion would suggest a fleet of 488 vehicles if they operated in the same fixed route manner. In the simulation experiment, we verify whether having demand responsive shuttles would reduce the fleet size required to serve under the same performance levels. To ensure robustness of our findings, we conduct multiple simulation runs to provide confidence bounds. This study serves as a practice-ready research reference for transportation planners considering different transit technology investments in a future where SAVs are viable alternatives.

2. DATA

For consistency, the data used to feed the simulation experiment comes from the assessment conducted by NYCEDC *[10]*. The following data and assumptions are used.

2.1. OD matrix

The demand forecasts for 2035 are based on NYC Department of Transportation's (NYCDOT) projections from planning for the SBS in NYC. Induced demand was assumed based on improved connectivity. The full OD matrix from NYCEDC *[10]* is shown in Table 1, which corresponds with the zones shown in Fig. 1. The OD patterns are distributed to the station level, with there being 30 stations. Stations are assumed to be uniformly distributed along the alignment. Trips going to external destinations like Manhattan are re-distributed to the station level. Lastly, the trips are factored to 8% of trips for the peak period.

2.2. BQX system parameters and performance benchmarks

The following information is from NYCEDC *[10]*. The BQX system is expected to operate on a 17-mile long alignment with approximately 30 stops operating 24 hours a day with minimum of 5-minute headways during peak periods. It would provide intermodal connections to 8 ferry landings, 37 bus routes, 17 subway lines, and 116 Citibike bike-share stations. The line will have an average operating speed of 10.5-10.6 mph, an end-to-end travel time of 81-82 minutes during peak periods, an assumed recovery time of at least 10 minutes at each end of the alignment, and a minimum dwell time of 20 seconds at each station.

Table 1. Full OD matrix used to derive demand patterns for simulation (source: NYCEDC *[10]*)

	Astoria	Ravenswood	Long Island City	Greenpoint	Greenpoint - South	Williamsburg - North	Williamsburg - Central	Williamsburg - South	Navy Yard
Astoria	232	154	368	15	13	3	0	0	27
Ravenswood	112	116	68	1	0	0	0	0	6
Long Island City	9	34	10	0	0	11	4	0	2
Greenpoint	0	40	11	28	2	0	0	29	80
Greenpoint - South	0	1	2	7	14	16	3	32	44
Williamsburg - North	0	13	27	14	3	23	11	13	42
Williamsburg - Central	1	24	23	12	2	39	13	0	62
Williamsburg - South	35	6	60	32	7	15	2	78	86
Brooklyn Navy Yard	11	19	26	11	55	6	6	23	155
DUMBO	0	8	0	0	0	0	0	1	6
Brooklyn Heights	0	6	41	10	1	10	4	8	40
Red Hook - North	0	17	17	0	6	22	8	3	87
Red Hook - South	0	6	0	23	6	5	5	12	143
Sunset Park	5	28	7	80	7	21	16	24	173
Sunset Park Terminal	41	51	56	78	13	15	1	12	196
Total	**445**	**523**	**717**	**312**	**129**	**187**	**75**	**234**	**1148**

	DUMBO	Brooklyn Heights	Red Hook - North	Red Hook - South	Sunset Park	Sunset Park Terminal	Manhattan	Other Brooklyn	Other Queens	Total
Astoria	51	91	1	0	0	2	12401	208	2197	15,762
Ravenswood	11	39	0	0	3	7	3570	117	1008	5059
Long Island City	14	26	0	1	4	2	2305	0	109	2531
Greenpoint	16	71	11	38	56	15	3142	546	183	4269
Greenpoint - South	27	38	5	45	4	5	3209	337	150	3939
Williamsburg - North	29	17	0	7	5	0	2788	182	50	3227
Williamsburg - Central	104	49	0	0	13	3	3205	397	220	4165
Williamsburg - South	54	64	13	10	52	65	1247	617	208	2650
Navy Yard	54	214	13	70	70	45	5224	1083	370	7455
DUMBO	35	33	8	18	48	0	2264	73	36	2532
Brooklyn Heights	63	180	21	19	13	32	7796	403	143	8789
Red Hook - North	76	154	61	71	42	9	4185	598	47	5404
Red Hook - South	117	243	37	82	92	34	4934	870	123	6733
Sunset Park	117	374	63	95	557	243	5757	2503	357	10,425
Sunset Park Terminal	108	296	35	117	370	145	4924	2113	572	9142
Total	**877**	**1888**	**269**	**573**	**1327**	**605**	**66,952**	**10,048**	**5772**	**92,081**

Travel times for certain routes are provided, including Astoria to Williamsburg (27 minutes), DUMBO to Red Hook (20 minutes), Long Island City to Red Hook (50 minutes), and Long Island City to Downtown Brooklyn (40 minutes). No overall passenger-weighted average travel time is provided.

2.3. Assumed SAV system parameters

The SAV system to be evaluated will run on the same length alignment and the same number of stops. It will operate at the same operating speed and minimum dwell times of 15 seconds. Since the autonomous vehicles do not require recovery time at the ends of the route, that is assumed to be zero. The fleet will run on vehicles with capacity of 12 people, which is consistent with the EZ10 vehicles from EasyMile. Three operating policies will be considered. These are chosen to distinguish between demand-responsive service and fixed route service, and to separate between idle vehicles waiting at stations versus waiting at garages located between stations.

A. Demand-responsive service with garages located between stations (BQX1v1)
B. Demand-responsive service with stations acting as garages for the shuttles (BQX1v2)
C. Fixed route service operating in the same way as the streetcar (BQX2)

The demand responsive service assumes a basic myopic policy: the closest available vehicle is assigned to a newly arrived passenger. Since more advanced policies also exist (see Sayarshad and Chow *[14]*), this myopic policy presents a conservative fleet requirement upon which more advanced algorithms can be applied to the SAV fleet. Scenario A with garages located between stations is illustrated in Fig. 3.

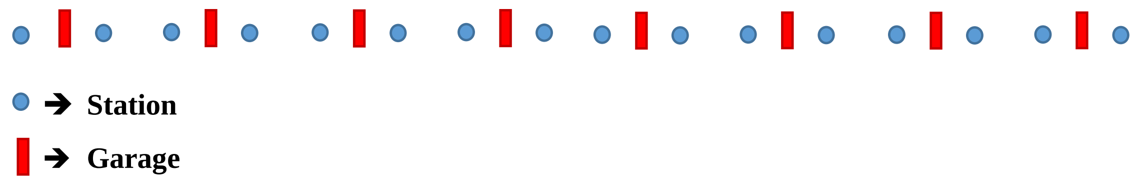


Fig. 3. Illustration of garages located between stations to park idle vehicles in the SAV scenarios.

3. EXPERIMENT DESIGN

The experiment consists of a simulation of the three SAV operating policies and comparing their performances to the baseline BQX streetcar. For consistency, the BQX streetcar line is also simulated in the same environment to determine the passenger weighted average wait time and travel time. By simulating the SAV scenarios over different fleet sizes, we can identify the fleet size required to serve the same user demand as the BQX streetcar service and under the same level of performance. This finding can help policy-makers in transit technology investments.

3.1. Simulation model

The simulation model generates passenger arrivals as a series of events over time and updates the locations of vehicles in the system based on prescribed operational policies. An overview of the simulation process is shown in Fig. 4.

The process shown in Fig. 4 is very similar to how the simulation of the demand-responsive case works. The fixed route simulation just has two events (shuttle arriving the station and shuttle leaving the station), while the demand-responsive case has a third event: passenger arrival. In this new event, a decision is made on which shuttle will pick the new passenger and the information of the route the shuttle has to follow. While in the fixed route simulation every shuttle has to stop at every station, in the demand-responsive case the shuttle just stops in the station in which it has to pick or drop some passenger.

For a given fleet size, the vehicles are evenly distributed over the garages at the start of the simulation. They then get dispatched according to an optimal headway based on the fleet size if running as fixed route simulation, or when a new customer arrives in a demand-responsive case.

A two hour period is simulated in one run, and the performance measures are kept for the middle hour to have a half-hour warm-up period. Multiple runs are conducted to obtain a sampling distribution for the simulated outputs.

Only the arrivals are random; they are generated using Monte Carlo simulation with exponential inter-arrival times based on the ridership demand.

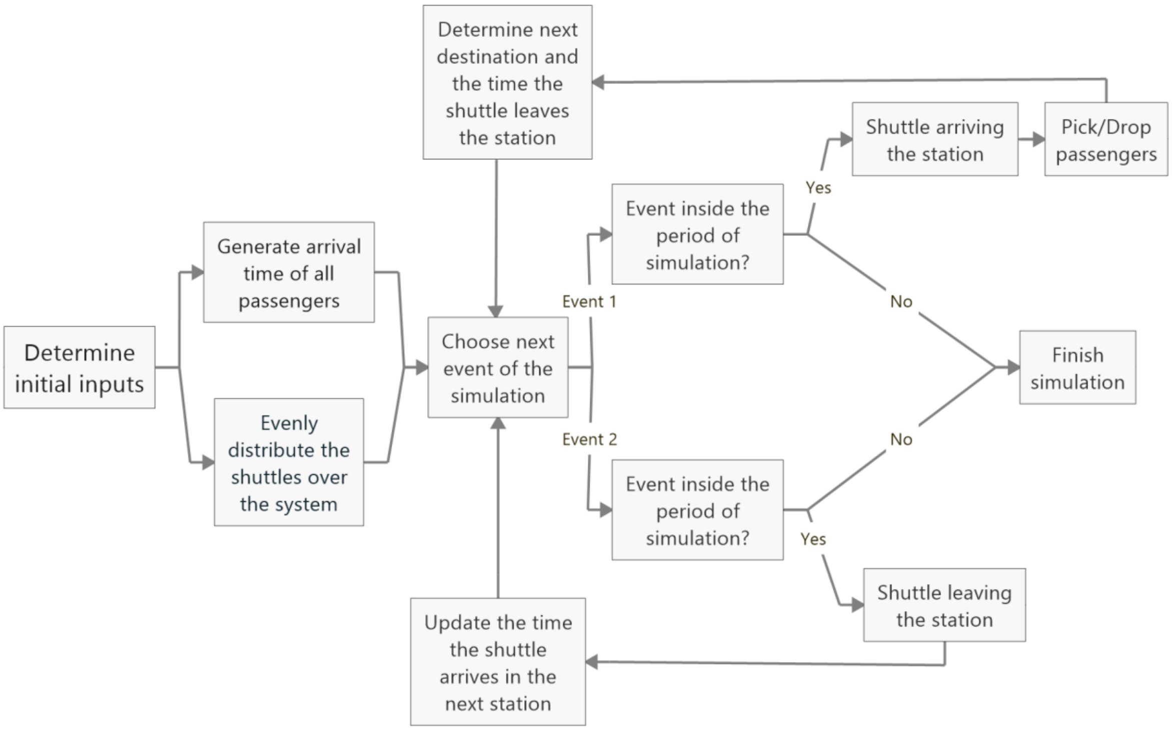


Fig. 4. Flow diagram of the fixed route simulation.

The simulation outputs the following variables:

- For each person n out of N generated arrivals that complete their trips
  - The time and station of entry into the system, time of boarding, and time and station of alighting
  - Computed wait time W_n and in-vehicle travel time T_n
- For each vehicle v in fleet V
  - Location in the corridor at time of each passenger arrival, boarding, and alighting event, passenger load of vehicle $Y_v(t)$ at time t – the load should never exceed the vehicle capacity K (set to be 12 for the SAVs, and 150 for the BQX streetcar)

For a single run, it is possible to get a population distribution of the wait time W and travel time T. Over multiple runs, it is possible to get confidence bounds of the population-average wait time $\overline{W}$ and travel time $\overline{T}$.

The simulation model is developed in MATLAB R2015b using an Intel® Core™ i7-6500U CPU @ 2.50GHz, 8.00 GB of RAM and using a 64-bit Windows 10. The average run time for a 2-hour run is 40 seconds for the demand-responsive case and 5 seconds for the fixed route simulation. Thirty runs are conducted for one scenario so that confidence intervals for the values can be obtained.

3.2. Computational scenarios

First, the BQX streetcar design is simulated using the Matlab simulation model. Ten runs are simulated to obtain a benchmark population average travel time and wait time for the OD demand. The other scenarios use these values to determine the adequate fleet size.

The three operational scenarios in Section 2.3 are simulated next. Each scenario is simulated for a range of different fleet sizes from 50 to 500 in 50 vehicle increments. For each fleet size, 10 runs are simulated so that a box plot can be constructed for the average values. This gives a robust assessment of the minimum fleet size to achieve the same performance as the 39 streetcars. Comparisons between operating policies can be made.

For the best scenario, a single simulation run is made to show the histogram of the wait time and travel time across the population. These results can be compared to the range of streetcar travel times provided by NYCEDC *[10]* from 20 to 52 minutes.

The simulation also provides an output of the simulated vehicle loads, so an analysis of the average loads can be conducted to evaluate the efficiency of the policy.

4. SCENARIO ANALYSIS

4.1. BQX streetcar operation as baseline scenario

In the baseline scenario, we simulate the streetcar operation with fixed route service, 39 vehicle fleet and 150 passenger capacity in each vehicle. With this result, we obtain the following simulation outputs from one run in Table 2.

Table 2. Performance measures from 10 runs of BQX fixed route LRT system

	Average	**Standard Deviation**
Wait time (minutes)	2.379	0.096
In-vehicle travel time (minutes)	20.068	0.146
Total time (minutes)	22.377	0.096

These numbers fit the range of values provided by NYCEDC *[10]*, as the total time falls within the numbers provided and the wait time of 2.379 minutes is approximately half the 5 minute headway. These numbers verify the simulation model and OD demand matrix's calibration.

4.2. Selecting the fleet size

We run 10 runs of each scenario A, B, and C and obtain box plots of the wait time and total time that includes in-vehicle travel time, across a range of fleet sizes from 50 to 500 vehicles. These values are plotted in Fig. 5 for the wait times and Fig. 6 for the total times.

Based on Fig. 5, it shows that a fleet size of 450 or more is needed to ensure that wait time is similar to the 5 minute headway LRT service. The three services feature high variations in performance when fleet size is small. This is indicative of an oversaturated system where passengers have to wait longer because a vehicle is over capacity upon arrival.

The 450 fleet size shows a significantly smaller variation in the average wait time, particularly for fixed route service. This makes sense since fixed route service under deterministic system parameters and travel times would have consistent availability for arriving passengers.

While the fixed route scenario C has more stable wait times at the higher end, it is also more vulnerable to small fleet sizes as wait times can reach 30 to 40 minutes. On the other hand, the flexible route scenarios don't appear to have wait times higher than 16 to 18 minute range. This is an important consideration in the case where disruptions cause a portion of the fleet to break down.

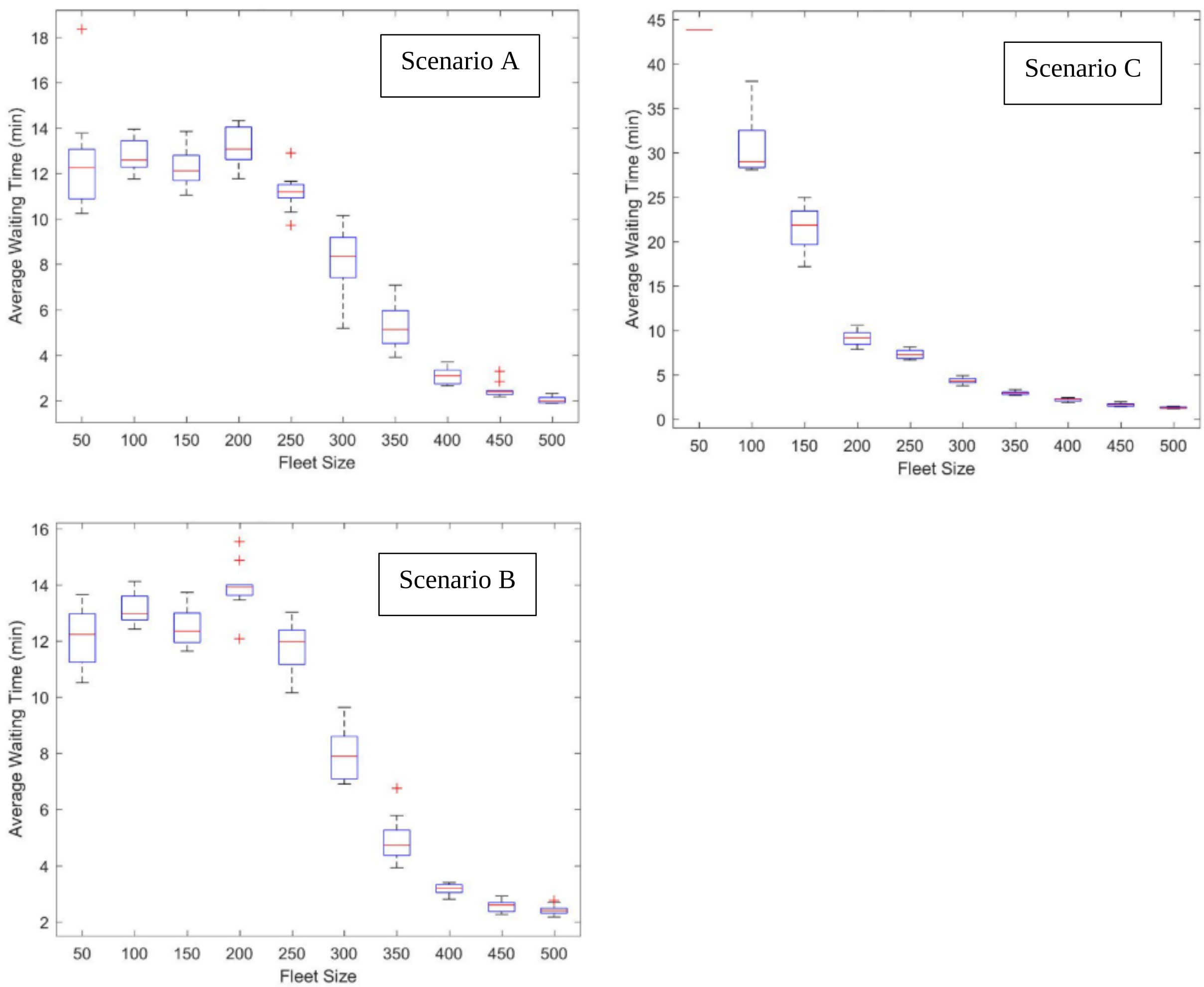


Fig. 5. Box plots of wait time for each of the three scenarios.

Fig. 6 shows that fixed route service using the small 12-person vehicles, a fleet size of 500 or more is needed to reach the same performance level as the LRT system, which has an average total time of 22 minutes. On the other hand, the flexible services can operate with generally 150 vehicles or more to reach approximately the same total time as the LRT. If both wait time and total time are desired, then a fleet size of 450 would be needed in the demand responsive flexible service cases. This also means that flexible service with 450 vehicle fleet would provide average total times of ~ 14 minutes, which is a 36% improvement in total time from the LRT system while maintaining the same average wait time. A fleet of 450 vehicles implies an average density of 26 to 27 vehicles per mile along the 17-mile corridor. Note that operating at 150 vehicles in scenarios A and B would have the same total travel time, although the wait time would have to increase from 2.5 minutes to 12 minutes. Since travelers tend to place a higher premium cost on wait time (about 1.7 times in-vehicle travel time) *[15]*, a cost effective solution should fall somewhere between 150 and 450 vehicles.

Between scenarios A and B, it appears that the location of the garages for parking idle vehicles does not have a significant impact. This verifies the early theoretical finding from Hakimi *[16]*, who noted that the optimal location of a facility can always be found at a node. Moving forward we use scenario A with fleet size 450 as the preferred, conservative alternative.

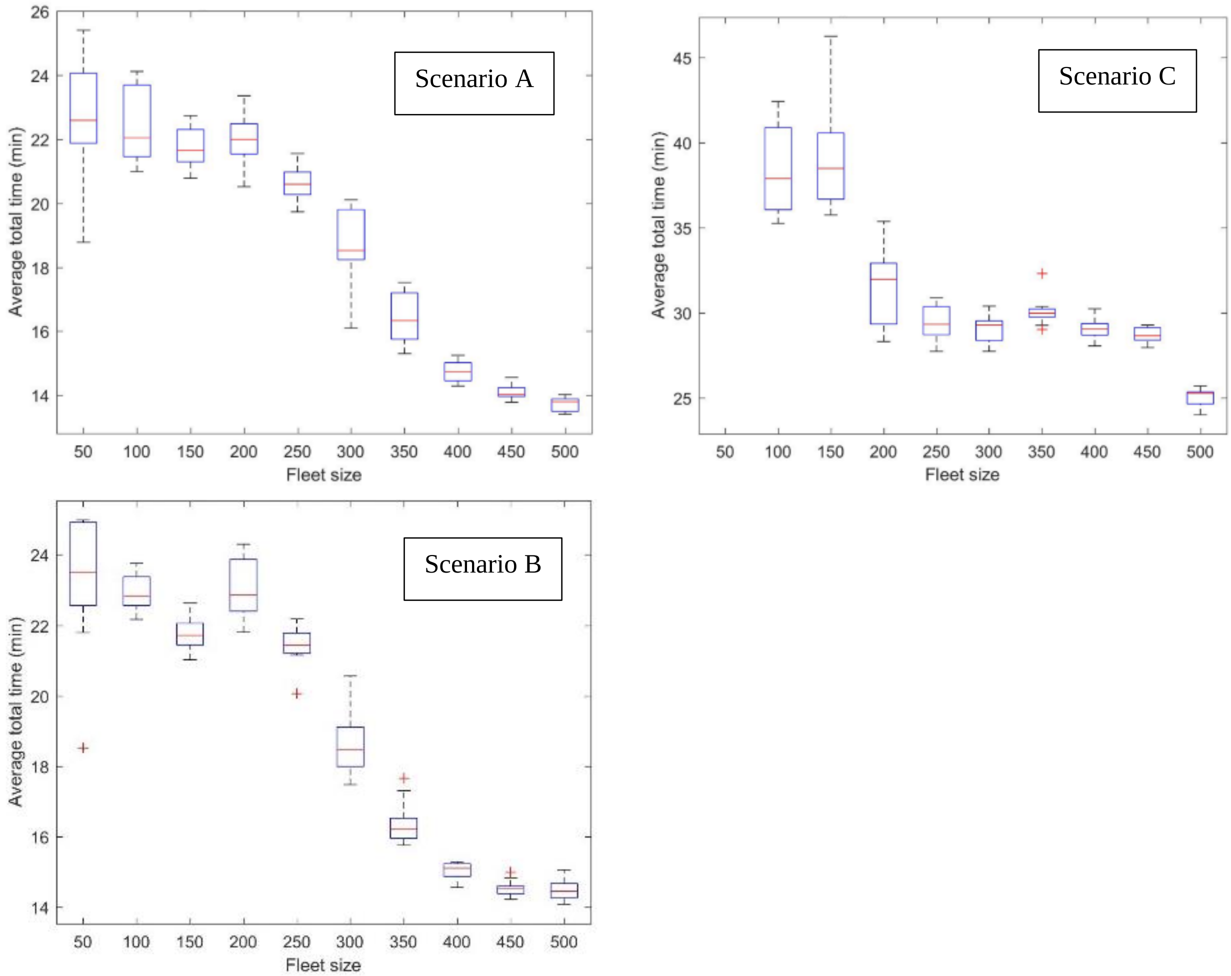


Fig. 6. Box plots of total travel time (wait time plus in-vehicle travel time) for each of the three scenarios.

4.3. Heterogeneity of service performance

We dig a little bit deeper in the analysis of the simulated SAV fleet. The distributions of the wait time W and total time $W + T$ across the population are plotted in a histogram in Fig. 7 from the output of one run using scenario A with a fleet size of 450.

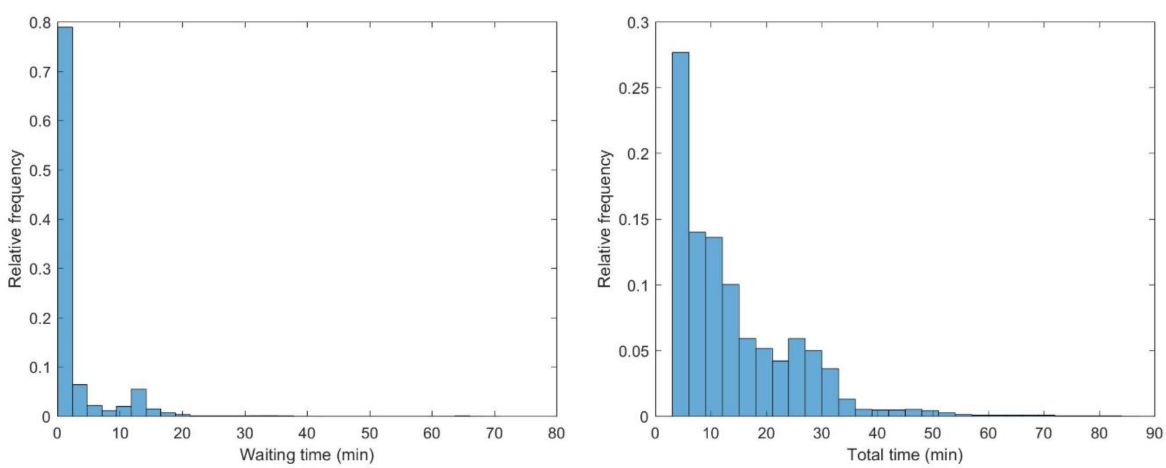
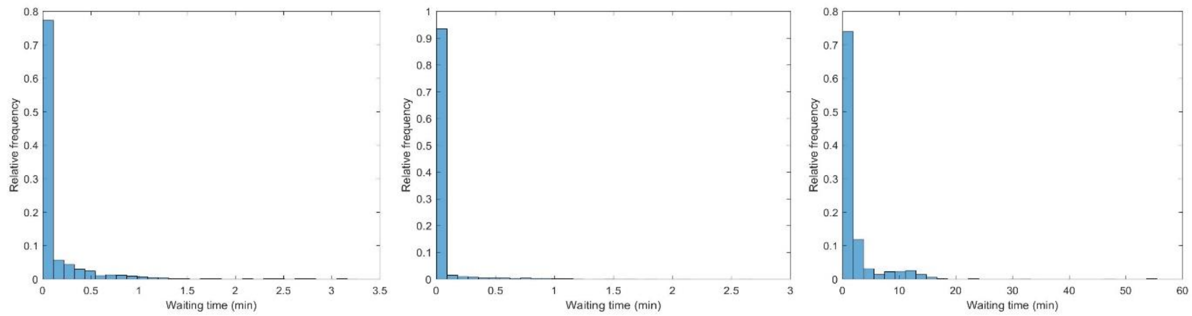


Fig. 7. Distribution of wait times and total times from one run of scenario A with fleet size of 450.

The distribution of passenger waiting time is also made for passengers that arrive at stations 5 (at Long Island City), 21 (at Brooklyn Heights), and 30 (at Sunset Park Terminal) because those were the stations with the highest OD demand. These are shown in Fig. 8.



Long Island City Brooklyn Heights Sunset Park Terminal

Fig. 8. Distribution of wait times at specific stations from one run of scenario A with fleet size of 450.

Fig. 8 illustrates the diversity of performance levels over different stations. Even though the arrivals are simulated as exponential inter-arrivals, it is interesting to see that some busier stations like Sunset Park Terminal (station 30) can exhibit a multimodal distribution.

4.4. Evaluation of vehicle load

The distribution of the vehicle loads over one simulation run for scenario A with 450 vehicles is also evaluated, as shown in Fig. 9. The figure shows that over the course of one run, the average passenger load among all vehicles is in the 4 passenger range, although some are operating mostly empty (at 0) and a small proportion are operating highly efficiently with more than 8 average passengers over its entire run.

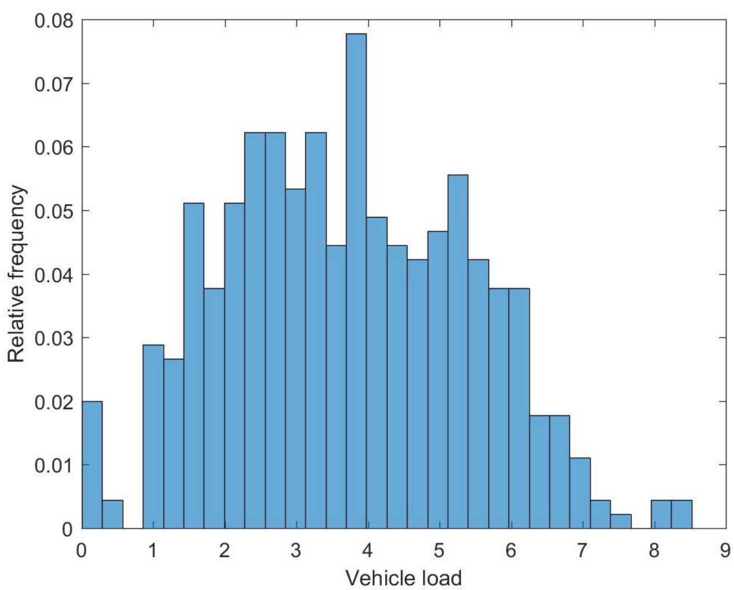


Fig. 9. Distribution of vehicle load over fleet of 450 vehicles for one simulation run in scenario A.

4.5. Policy implications

Transit technology selection depends highly on the density of demand and the coverage area. In this particular instance, the OD demand and route suggests that the use of smaller capacity vehicles like the EZ10s in a fixed route operation would require a significant fleet size of 500 or more to meet the same performance level of an LRT fleet of 39 vehicles during the peak period. However, a flexible service would only require 450 or less vehicles, with equivalent total time achievable with 150 vehicles. This finding from a direct comparison between SAV fleet operations and a proposed LRT fleet should give policymakers a viable alternative to consider.

The analysis also provides policy-makers with tools to evaluate trade-offs between fleet costs and users' wait time, as increasing fleet size from 150 to 450 would reduce wait time. This trade-off can be used to design fleet size needs for off-peak periods, particularly since the LRT system is expected to operate with 10 to 20 minute headways in off-peak periods, which translates to average wait times of 5 to 10 minutes. For example, scenario A operations with fleet size of 250 vehicles would have average wait times at 10 minutes.

The heterogeneity in the station performance suggests that allocation of idle vehicles should depend on the demand at each station. Particularly in the case of the demand responsive service, allocations based on this information could lead to improved system performance. This can be achieved by having idle vehicles in scenario A and B move to the "closest" demand-weight station. For example, a station 1 may be 500 ft away while a station 2 may be 1500 ft away, suggesting an idle vehicle should relocate to station 1. However, if station 2 has observed average wait time that is 4 times higher (e.g. 12 minutes as opposed to 3 minutes at station 1) then a weighted comparison could be $\frac{500}{3} = 166.67$ at station 1 versus $\frac{1500}{12} = 125$ at station 2. This would suggest a closer "effective" distance for relocation to be at station 2. This relocation policy can also be tested in future research.

5. CONCLUSION

A comparative study was conducted between a hypothetical SAV fleet and a LRT street car system proposed by NYC. This is the first such study for SAV fleets, and also the first third party evaluation of the system proposed by NYC. Considering that the proposed LRT system costs significantly higher than an SBS system but operates approximately the same, an additional comparison is warranted particularly since an SAV fleet would be even more tourist-friendly than a streetcar. The experimental findings suggest that an SAV fleet of 150 vehicles that operates even a basic myopic demand-responsive policy can achieve the same total time as the fixed route LRT system. Increasing that fleet size to 450 would result in the same average wait time as the LRT operating with 5-minute headway, while operating at 36% reduced total time. These findings encourage further study of SAV technology as a viable alternative.

The simulation of the SAV fleet conducted in this study assumes simple operating policies. More advanced policies can also be evaluated in future research: non-myopic dispatch and routing of vehicles to serve passengers (see *[14]*); relocation of idle vehicles; predictive modeling of passenger arrivals (see *[17]*); holding strategies for vehicles; and pricing strategies. Adding these other policies would further decrease the fleet size requirement.

The SAV simulation studies thus far, including this study, do not consider unique advantages of SAV fleets. For example, SAV fleets continuously sense and observe from their surrounding environments, so there is an advantage to learning under stochastic environments. Second, SAV fleets do not have drivers so it's possible for vehicles to platoon together. This modular property of vehicles enables them to flexibly adapt the vehicle size and headway to handle different demand levels *[18]*. Third, SAV fleets can be pre-programmed with travel and activity patterns of travelers so that they can anticipate the need for travel hours in advance when allocating vehicles, and may allow travelers to reserve time slots for their use *[19]*. Because the prior simulation studies have not considered these cases, they operate the same as driver-based demand responsive transit services. A number of studies in these have been conducted in the past, which should also be acknowledged: examples of driver-based simulation studies of demand responsive services include Horn *[20]*, Cortés et al. *[21]*, Agatz et al. *[22]*, Jung and Jayakrishnan *[23]*, and Djavadian and Chow *[24]*. A further extension for future research is to evaluate the performance of SAV fleets when they consider the unique advantages that driver-based fleets do not have.

ACKNOWLEDGMENTS

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