Submitted to *INFORMS Journal on Applied Analytics*
manuscript (Please, provide the manuscript number!)

The University of Michigan Implements a Hub-and-Spoke Design to Accommodate Social Distancing in the Campus Bus System under COVID Restrictions

Gongyu Chen, Xinyu Fei, Huiwen Jia, Xian Yu
Department of Industrial and Operations Engineering, University of Michigan at Ann Arbor, USA,
chgongyu,xinyuf,hwjia,yuxian@umich.edu

Siqian Shen
Corresponding author; Department of Industrial and Operations Engineering, University of Michigan at Ann Arbor,
siqian@umich.edu

The outbreak of coronavirus disease 2019 (COVID-19) has led to significant challenges for schools and communities during the pandemic, requiring policymakers to ensure both safety and operational feasibility. In this paper, we develop mixed-integer programming models and simulation tools, to re-design routes and bus schedules for operating a real university campus bus system during the COVID-19 pandemic. We propose a hub-and-spoke design and utilize real data of student activities to identify hub locations and bus stops to be used in the new routes. To reduce disease transmission via expiratory aerosol, we design new bus routes that are shorter than 15 minutes to travel and operate using at most 50% seat capacity and the same number of buses before the pandemic. We sample a variety of scenarios that cover variations of peak demand, social-distancing requirements, and bus breakdowns, to demonstrate the system resiliency of the new routes and schedules via simulation. The new bus routes were implemented and used during the academic year 2020-2021 to ensure social distancing and short travel time. Our approach can be generalized to redesign public transit systems with social distancing requirement to reduce passengers' infection risk.

Key words: Bus routing and scheduling, integer programming, simulation, social distancing, COVID-19 pandemic
History:

Introduction

The University of Michigan (UM)'s fleet of buses provided an estimated 8 million rides between its three campuses in 2019 (Michigan News 2020). In an effort to design a safe campus bus system for the Fall semester of 2020 in light of COVID-19, researchers at UM simulated how aerosol particles exhaled from passengers sitting in any seat would travel through the interior of a campus bus (see Zhang et al. 2021). In that work, physics-based computer models of aerosol dispersion were developed under different social-distancing and bus-operating conditions, and the results were validated with experiments using water vapor in a real bus. To minimize passengers' possible exposure to the virus, all bus passengers and drivers must wear face coverings, and the capacity of buses also needs to be reduced to half of the original capacity or even lower, while the length of each trip needs to be limited to 15 minutes or less.

However, the pre-pandemic campus bus system at UM uses long routes that were designed to minimize transfers. Some routes (e.g., the original Commute South, Commute North and Northeastern Shuttle) take 45 minutes to 1 hour to travel even without including the passenger loading/unloading time at each bus stop. Simply breaking down the original long routes into shorter ones will significantly increase the number of buses needed to cover all the original demand, especially when only half bus capacity can be utilized. Meanwhile, it is not possible to add more buses and drivers due to the high cost of purchasing a campus bus (approximately $800,000 each) and the difficulty of retaining and hiring qualified drivers during the pandemic, according to our conversation with the UM campus transit operational team (Dolen et al. 2020). Thus, the goal is to design a safe bus transit system by operating routes that use most 50% seat capacity and have a duration of at most 15 minutes, using the same number of buses in the pre-pandemic system to satisfy all the campus travel demands.

To accomplish the goal, we develop a mathematical optimization model and a simulation platform to design a hub-and-spoke system that relies on short, direct routes with fewer stops. We show in our numerical studies that, the new routes not only limit all the rides to 15 minutes or less, but also enable more frequent service using the same number of buses, and therefore reduce passenger wait time as well as the number of passengers on each bus. We conduct result validation via simulation by generating a diverse set of scenarios that take into account spatial-temporal variations of demand, changes of social-distancing requirements, and random bus breakdowns (or equivalently driver no-shows). The simulation results not only show that we achieve the goal given by UM bus operators, but also verify that all the riders can find a bus stop within 5 minutes of walking distance and 70% of passengers still take only one bus transfer for completing their trips. For 35% of passengers, the average waiting time is less than 5 minutes. For 70% of passengers, the average waiting time is less than 10 minutes. We also identify the routes that have higher utilization on average or during peak hours, and the bus stops that have longer average waiting time. To improve the system resilience, we develop contingency plans of moving buses to these routes from others in case of certain bus failures. The new bus routes were used by UM during the academic year 2020-2021 (U of Michigan Campus Transit 2020, Michigan Engineering News 2020). Compared to the pre-pandemic route design, students were able to spend less time on buses and there are consistently fewer riders on each bus.

Literature Review

Our paper is related to prior work on transit network planning, including transit network design (see, e.g., Yu et al. 2012, Ouyang et al. 2014), transit network timetabling (see, e.g., Ibarra-Rojas and Rios-Solis 2012, Fonseca et al. 2018), vehicle scheduling problem (see, e.g., Naumann et al. 2011, Yan et al. 2012), and transit network evaluation (see, e.g., Chandrasekar et al. 2002, Zhang et al. 2019).

In particular, the transit network design (TND) problem determines the lines, types of vehicles, and stop spacing to meet population's movement requirements. Yu et al. (2012) use a direct traveler density model (first proposed in Yang et al. 2007) to maximize route utilization under resource constraints. Kim and Schonfeld (2014) propose a probabilistic analytical model to design and synchronize a bus transit network by integrating conventional and flexible bus services and coordinating bus arrivals at transfer terminals. We refer to Guihaire and Hao (2008) for a comprehensive review of TND problems, where some limit route length in the network design, similar to the 15-minute travel limit in our problem.

In terms of transit network planning (TNP), Desaulniers and Hickman (2007) conduct a survey on mathematical methods used for individual steps of strategic, tactical, operational planning, as well as real-time control related to TNP. Ibarra-Rojas et al. (2015) comprehensively review the TNP literature and real-time control strategies suitable to bus systems. Ceder (2016) summarizes efficient solutions of TNP and discusses how to model operations in practice including bus loading/unloading time and passenger behavior.

The methods we use for redesigning campus bus routes are based on the hub-spoke design (also referred to as hub location problems, see, e.g., Campbell and O'Kelly 2012). Campbell et al. (2002) and Farahani et al. (2013) provide comprehensive review on mathematical models, solution methods, and applications of hub-spoke systems. Aykin (1995) considers the hub location-routing problem, where hub locations and routes linking demand points to the hubs need to be determined together. The paper provides a mathematical formulation and an iterative algorithm for solving the hub location and the routing subproblems separately. Rodríguez-Martín et al. (2014) propose a mixed-integer programming formulation for the hub location-routing problem and develop valid inequalities used in branch-and-cut algorithm for optimizing instances with up to 50 nodes. Lopes et al. (2016) describe various heuristic methods for solving larger-sized instances of the hub location-routing problem.

Route Design

Model Setup

We describe the details of a mathematical programming model to configure new bus routes in a hub-and-spoke design. Before building the model, to inform our design, we first gather 2019-2020 school year student activity data, including schedules and sizes of different types of classes and main student activities, utilization of facilities (gyms, dining halls, libraries, etc.), student dormitory locations, numbers of on-campus and off-campus residents, student majors and their school years, as well as typical courses taken by different majors during each of their school years. Because some staff and faculty use campus buses to travel from certain parking lots to workplaces, we also gather information about parking lots' locations and typical utilization throughout a day. To estimate demand generated by the medical school, we also gather all the UM medical school's related data including time of shifts in each hospital and clinic, as well as their faculty, staff, and students' schedules. Using all these data, we estimate the average demand between pairwise locations on campus during different hours of each school day (from Monday to Friday). We associate these locations to existing bus stops in the old UM bus system (which are 110 stops), and identify the stops that are within 5-minute walking distance to each location. We identify the hub location on each of the three UM campuses as the location on the respective campus that has the largest origin or destination travel demand during the most hours of every day. In later sections, we use the same real-data sources to estimate demand between origins and destinations, to determine bus frequency, and to evaluate the performance of each route using simulation.

In Figure 1, we show a hub-and-spoke system with three hub locations (represented by squares) in the UM North Campus, Central-South Campus and Medical Campus, respectively. In our new design, a Campus Connector route will connect these hubs with frequent

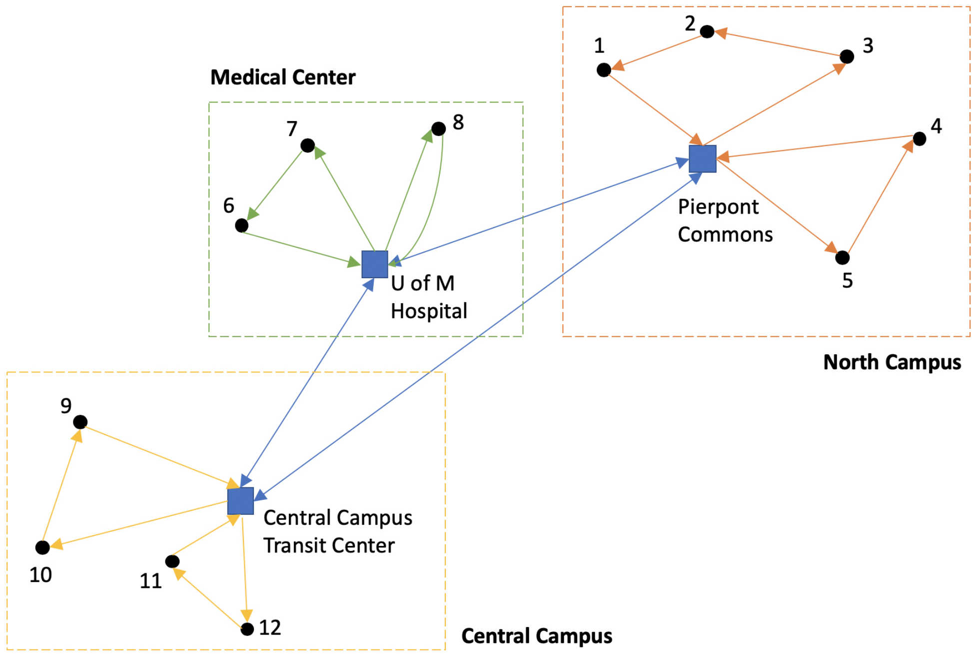


Figure 1 **An illustration of the hub-and-spoke system for operating UM buses in all its Ann Arbor campuses**

buses. Next, we design routes to connect popular bus stops within each of the three campuses (i.e., sub-regions) from and to their corresponding hubs.

Route Solution Description

We formulate a mathematical optimization model using mixed-integer programming for designing bus routes originating from and returning to each hub location, and refer the readers to the details in the Appendix. We code the mixed-inter programming model (i.e., Model (3) in the Appendix) using Python and solve it using the Gurobi solver 9.0.3. Our numerical tests are conducted on a Windows 2012 Server with 128 GB RAM and an Intel 2.2 GHz processor. In total, we are given 110 bus stops from the pre-pandemic bus system and Model (3) will optimize the bus stops used in the new design and how to connect them.

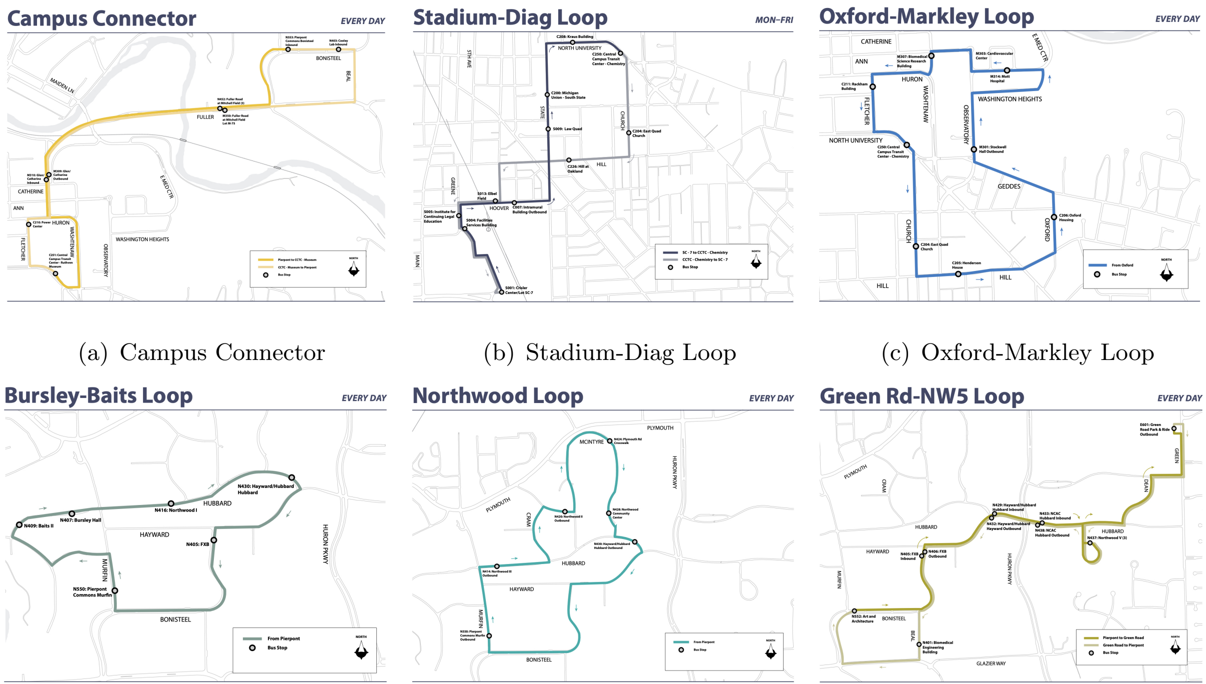
After solving Model (3), there are in total 50 stops picked to form five different routes (three in North campus and two in Central campus), together with the route that links all the three hubs. We present optimal routes produced by Model (3) in Figure 2 and individual routes with detailed stops in Figure 3. Among these six routes, Bursley-Baits Loop, Northwood Loop and Green Rd-NW5 Loop operate in the North Campus of UM, while Oxford-Markley Loop and Stadium-Diag Loop operate in the Central Campus. The

Campus Connector operates in between respective hubs in the North and Central campuses. The CPU times for finding three routes in North Campus and two routes in Central Campus are 11.19 seconds and 9.74 seconds, respectively. Because the Medical Campus is located in between the North and Central, the hub in the Medical campus is on the Campus Connector route connecting the North and Central campuses, and its nearby bus stops are assigned to routes associated with the other two hubs.

Figure 2 **Optimal routes obtained by solving Model** (3) **for designing a hub-and-spoke system.**

Bus Frequency Design

Next, we describe how to design the number of buses and frequency for each new route shown in Figures 2 and 3. The goal is to satisfy traveler demand using the same number of buses used previously, while ensuring social distancing and shorter travel time. We are given two types of buses: The first is a shuttle with 35 seats that was used on the old North-East route pre-pandemic, and the second is a bus with 78 seats that was used on other routes in the old system. (In our calculation, we use 70 instead of 78 as the capacity of the latter type, because some seats could be unavailable due to the need of distancing passengers and the driver, as well as stocking personal protective supplies such as masks and also disinfectant wipes in some seating area.) The bus stops on our new Green Rd-NW5 Loop overlap with the ones on the old North-East route and therefore, we will use the 35-seat shuttles only on the Green Rd-NW5 Loop.



(a) Campus Connector (b) Stadium-Diag Loop (c) Oxford-Markley Loop

(d) Bursley-Baits Loop (e) Northwood Loop (f) Green Rd-NW5 Loop

Figure 3 Individual routes and bus stops used in the UM 2020-2021 bus transit system.

For each new route, we first obtain its estimated round-trip traveling time (as the sum of the total driving time and passenger loading/unloading time). Note that each of our new routes is passed through by multiple routes in the old system. Therefore, to compute a frequency for a new route, we examine all the old bus routes that pass through each stop in the new route. Note that not all the bus stops in a new route have the same frequency in the old system, and we use the one that has the highest frequency to match. For each new route j, we denote $1/f_j^{\text{old}}$ (as the number of buses per hour) as the old system's highest frequency on any of its bus stops. For example, if a bus stop has two old routes covering it, each running every 20 minutes. Then, the old system's frequency on this bus stop and thus in any new route that contains this bus stop will be at least every 10 minutes and $1/f_j^{\text{old}} = 6$ buses per hour.

Now, with only C seat capacity available on each bus, where $0 \le C \le 100\%$, to have the same frequency of buses passing each stop in the old system, we need $(1/f_j^{\text{old}}) \times (1/C)$ buses per hour. (For example, if using only $C = 50\%$ seat capacity, then we need to run 12 buses per hour to achieve the same level of total passenger load.) Then, if the round-trip time of a route that contains the bus stop is 15 minutes, i.e., 0.25 hour. Then, we only need 3 buses on this route to achieve 12 buses per hour frequency on the corresponding bus stop.

REMARK 1. For some bus routes, the bus frequency varies depending on different times of a day in the old system, and we perform the above analysis for all bus stops and their corresponding new routes during all peak hours. Some bus stops may be involved in more than one route in the new system, and therefore, their frequency in the old system will be used for determining the frequency and the number of buses needed in multiple routes in the new system.

Lastly, we verify that the numbers of buses and shuttles needed for fulfilling the desired frequency on each new route do not exceed the total number of buses and shuttles in the current system. If more buses or shuttles are needed in the new system, one can apply heuristic methods to reduce the number of buses in relatively less busy routes during peak hours. In our later simulation studies, we find that our system is resilient to bus breakdowns and we also leave buffer when computing n_j by rounding up fractional numbers. We also need to make sure that the number of available drivers during different shifts between 6:30am and 1:30am (the next day) can cover all the buses needed in those shifts. The driver scheduling is completed by a third-party company that the UM transit department hires and is not in the scope of this paper. If more drivers are desired for certain periods, the University usually hires student drivers at the beginning of each semester as backup drivers.

Result Validation and Improvement Using Simulation

Framework and Main Logic

We validate and improve the performance of the new system using discrete-event simulation. For each bus stop, we define three related areas: wait area (WA), load area (LA), and unload area (UA). Buses arrive at each hub according to given frequency during different hours and move cyclically along the route paths. At each stop, buses unload passengers at UA, move to LA and load passengers from WA, and then leave for UA of the next stop along the route path. A passenger entity, who either gets off a bus or newly enters the system, will arrive at UA of the stop. The entity will decide whether to leave the system, to wait at WA, or to move to a nearby stop for taking another bus (i.e., a transfer) for continuing a trip. A passenger moves from WA to LA when a bus with sufficient capacity arrives and if the passenger needs to get on the bus. We summarize “Variables” and entity-specified “Attributes” of the simulation model in Table 1.

Table 1 Attributes and variables of the simulation model

Variables
stopID: ID associated with each in-use bus stop;
currStop: stopID of the bus stop where an entity currently stays;
maxCap: the maximum number of passengers a bus can hold.
Bus-related Attributes
currCap: number of passengers in a bus of interest;
Route: route ID of the bus.
Passenger-related Attributes
origin: stopID of the origin bus stop of a passenger;
dest: stopID of the destination stop that the passenger is moving towards.

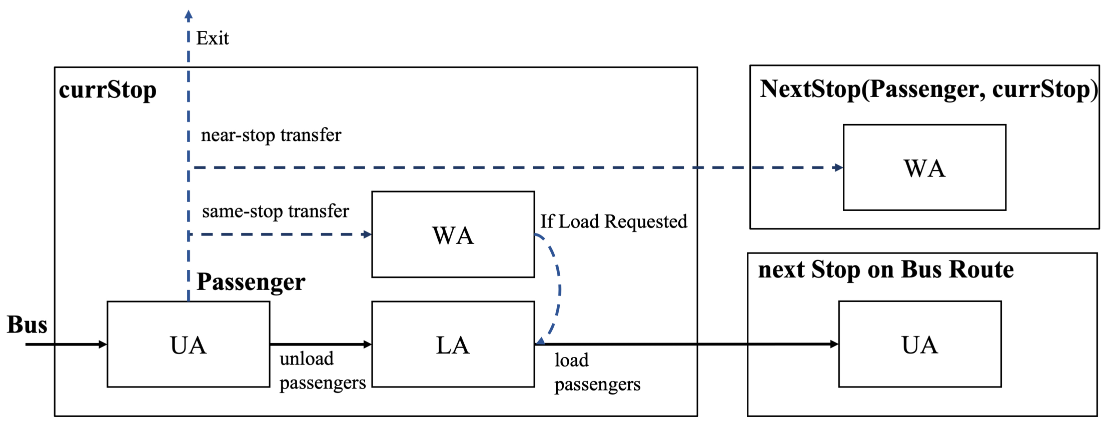


Figure 4 An illustration of the overall simulation process.

We demonstrate the overall logic for simulating actions of buses and passengers in Figure 4, and provide more detailed algorithmic flows of the simulation in Algorithms 1 and 2 in the Appendix. Passengers enter the bus system by arriving at their origins and move with buses to reach their destinations. The system must know at which bus stop a passenger can get off and which bus the passenger can take. In addition, a passenger may take a transfer at some stop if the origin and destination are on different routes. In this case, the system needs to select a stop for the passenger to wait. These decision-making processes are achieved by solving for the shortest path between the passenger's origin and destination through methods such as the Dijkstra's algorithm (see, e.g., Ahuja et al. 1993). Functions GetOn, GetOff, and NextStop shown in Algorithm 2 in the Appendix use the shortest path and the current stop to determine if a passenger needs to get on a bus, get off a bus, or select a stop to wait/exit, respectively.

Inputs and Parameter Settings

We consider the six routes given by Model (3), their frequencies, and the number of buses assigned to each route. We present detailed stops on the six routes, their travel time and the bus stop time in Tables 4–9 in the Appendix. The actual stop time of a bus at each stop in our simulation follows the following rules: It waits 1 minute if it needs to load/unload a passenger. It waits 2 minutes at the two hubs (in Central and North campuses) or at a stop having > 10 passengers who need to be loaded to or unloaded from the bus. These numbers are estimates from UM campus transit system operators and based on their experiences.

In the simulation, we focus on two 2-hour periods: 8am-10am and 12pm-2pm, "the busiest hours in either Fall or Winter semester at UM during pre-pandemic years." In addition to bus operations metrics (e.g., utilization and operating time), we are also interested in measuring the passenger-related metrics, including their aggregated waiting time and the number of transfers needed for completing their trips.

The mean and variances of the exponentially distributed random arrivals capture the variability in the volumes of passengers at different stops, and they are based on real UM student activity data in 2019. The 8am-10am and 12pm-2pm periods we test contain key epochs such as class starting and ending time and we sample random arrivals of passengers following an exponential distribution with mean computed from empirical data. On average, we have 1750 passengers arriving at all stops per hour (during 8am-10am or 12pm-2pm) in pre-pandemic semesters. In our baseline case (Case 1), we test the aggregated demand $D = 2625$ as 1.5×1750 in our baseline case, and consider $C = 50\%$ capacity (i.e., 35 seats per bus). As benchmarks, we test two other scenarios, Case 2 with $C = 25\%$ and $D = 1500$ (i.e., reduced demand from pre-pandemic years) and Case 3 with $C = 25\%$ and $D = 2625$.

We use the percentages of Origin-Destination (O-D) pairs shown in Table 10 and Table 11 (in the Appendix) for generating passenger arrivals and their trip destinations for 8am-10am and 12pm-2pm, respectively. The O-D pair distributions are based on the analysis of number of residents in different student dorms, their majors, daily activities, and course schedules in 2019-2020. We use 88% of the total demand D in each case multiplied by the O-D distributions in Tables 10 and 11 to compute the mean values of the exponentially distributed arrivals at each origin and their destination distributions for sampling passenger arrivals. Additionally, 12% of the total passengers will randomly arrive at one of the 44 stops and get off at any of the other 43 stops with equal probability. Passengers can make transfers at the same bus stops or sufficiently nearby stops immediately. Some pairs or triples of stops are considered to be within walking distance, so that passengers can make a transfer within 0.5 minute. In the Appendix, we present the list of bus stops that allow same-stop transfer in Table 12 and the list of bus stops that allow nearby-stop transfer in Table 13.

We test the new bus system's performance for the three aforementioned cases with different choices of C and D. We also conduct tests about the system's resilience when there is a random bus breakdown on any of the six routes. We run 40 replications for each case. To gauge operational performance, we use two metrics: (1) U_s = average utilization rate per stop-to-stop trip, and (2) $S_{0.75}$ = percentage of stop-to-stop trips with at least a 75% or above occupied seats. A stop-to-stop trip is defined as bus travel from a stop to the next stop along a route. When a bus leaves a stop, we compute its utilization rate as $U = \frac{\text{currCap}}{\text{maxCap}}$, and then calculate U_s by averaging the U-values over all the stops that buses have serviced. To obtain $S_{0.75}$, we count the percentage of stop-to-stop trips that have their $U \geq 75\%$.

For passenger-related metrics, we focus on the time each passenger spends in the system on average and how many transfers they take to complete their trips. We also measure the average wait time of each passenger spent at each bus stop. If a passenger needs to transfer to a different bus, the wait time is the sum of wait time at all the transfer stops. The time to walk to nearby stops is also included in the wait time.

Result Analysis

In Table 2, we show the results related to bus operations and passenger-related performance measures for Cases 1–3. The maximum utilization of buses/shuttles on any of the six routes is around 60%–70%, which satisfies the social-distancing requirement given in Zhang et al. (2021) for public transit systems. In addition, no more than 54% of buses or shuttles load more than 75% of its capacity in all three cases. Although increased D- and decreased C-values result in higher utilization of buses on each route, the differences are not significant. This justifies that the new system will not be overloaded even if we decrease the seat capacity further from $C = 50\%$ to 25%. Overall, the average number of passengers who take one or multiple transfers is around 20% and the average on-bus time of each passenger is

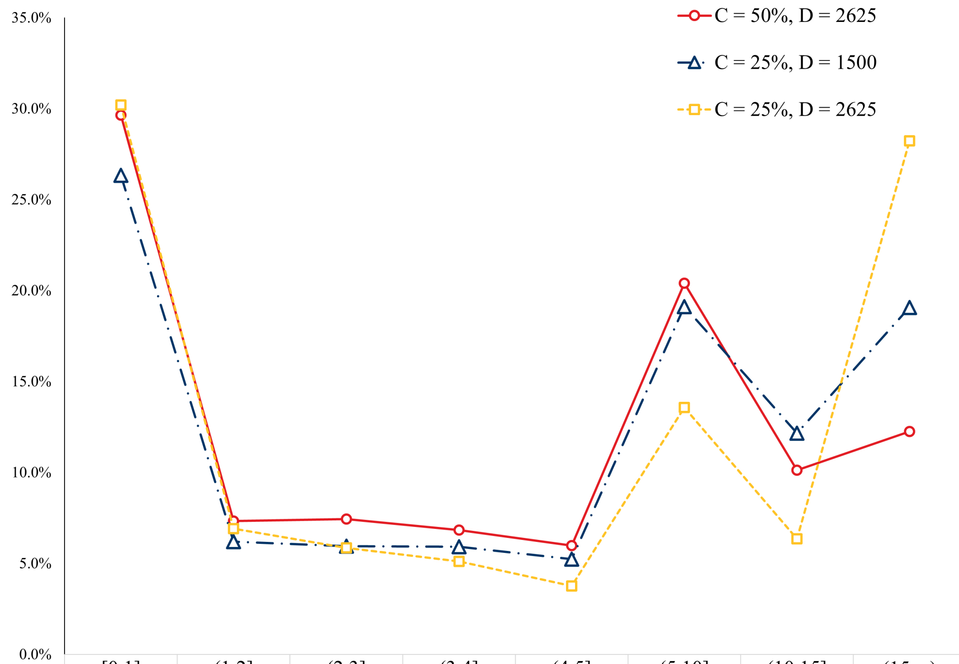
Table 2 Results of bus- and passenger-related performance measures for Cases 1-3.

Test Case	1	2	3
Seat Capacity (C)	50%	25%	25%
Total Demand (D)	2625	1500	2625
Bus Capacity Utilization U_s			
All routes	0.38	0.40	0.49
Campus Connector	0.25	0.27	0.33
Stadium-Diag Loop	0.10	0.11	0.19
Oxford-Markley Loop	0.32	0.35	0.54
Green Rd-NW5 Loop	0.51	0.51	0.53
Bursley-Baits Loop	0.62	0.64	0.70
Northwood Loop	0.38	0.40	0.49
Percentage of Overloaded Buses $S_{0.75}$			
All routes	0.09	0.13	0.33
Campus Connector	0.49	0.51	0.57
Stadium-Diag Loop	0	0	0.01
Oxford-Markley Loop	0.39	0.39	0.40
Green Rd-NW5 Loop	0.50	0.51	0.52
Bursley-Baits Loop	0.15	0.17	0.19
Northwood Loop	0.23	0.25	0.34
Passenger-related Results			
Avg. total travel time (min)	19.29	20.68	26.59
Avg. wait time (min)	6.78	8.42	14.46
Avg. on-bus time (min)	12.51	12.26	12.13
Avg. number of transfers	0.25	0.25	0.25
% who make transfers	20.10%	20.20%	20.00%

between 12–13 minutes in all three test cases. However, the average waiting time increases to 14.46 minutes from 6.78 minutes if we reduce the seat capacity from 50% to 25%.

In Figure 5, we further investigate passengers' wait time distribution in the three cases for 8am-10am and present the percentages of passengers waiting for different amounts of time. In all three cases, the average wait time is less than 15 minutes. More than 50% of the total passengers wait less than 5 minutes. Only 1 passenger in 5 needs at least one transfer to complete a trip. In the third case when $C = 25\%,\ D = 2625$, there is about 30% of passengers waiting longer than 15 minutes, which leads to significantly longer average waiting time for Case 3 depicted in Table 2.

Next, we perform stress tests by randomly breaking down one bus (i.e., reducing the total number of buses by one) on one route in each case. Using Case 1 ($C = 50\%,\ D = 2625$) as the baseline, we present statistics of passenger-related performance measures in Table 3.



	[0,1]	(1,2]	(2,3]	(3,4]	(4,5]	(5,10]	(10,15]	(15,∞)
C = 50%, D = 2625	29.6%	7.3%	7.4%	6.8%	6.0%	20.4%	10.1%	12.3%
C = 25%, D = 1500	26.3%	6.2%	5.9%	5.9%	5.2%	19.1%	12.2%	19.1%
C = 25%, D = 2625	30.2%	6.9%	5.9%	5.1%	3.8%	13.6%	6.4%	28.2%

Wait time (unit: min)

Figure 5 Percentages of passengers for different lengths of wait time in the three test cases.

Table 3 Results of one bus breakdown on each route for Case 1 when $C = 50\%$ and $D = 2625$.

Metric	Baseline	Campus Connector	Stadium-Diag	Oxford-Markley	Green Rd-NW5	Bursley-Baits	Northwood
Avg. total travel time (min)	19.29	19.35	19.49	20.14	19.60	19.37	18.33
Avg. wait time (min)	6.78	6.95	7.06	8.02	7.19	6.92	6.19
Wait ≥ 5 min (%)	42.78%	43.57%	43.63%	47.81%	44.90%	43.26%	46.61%

The performance results in Table 3 are similar to the ones in Table 2 and Figure 5 for all three test cases, which implies that the system is insensitive to small changes of bus availability on any route and it is resilient to capacity reduction.

Post-Implementation Discussion

The purpose of the simulation was to verify whether the new routes in the hub-and-spoke design can possibly handle demand if they were as high as pre-pandemic time. We report the results of bus utilization and travelers' experiences (such as waiting time and number of transfers they take) to show the consequences of shortening all the routes and reducing the usable bus capacity. The new bus system was implemented at University of Michigan (UM) Ann Arbor campuses in Fall 2020 and Winter 2021 semesters, during which, individual passengers' riding time, waiting, and transfer time were reported comparable to the simulation results, while bus utilization rates were much lower because the actual demand during 2020-2021 was much lower than the estimated demand used in the modeling. The buses mainly served demand from medical school and we were able to ensure 50% or lower bus capacity use to allow social distancing during peak hours. The hub-and-spoke design meets the requirements from UM policymakers during the most severe months of the COVID-19 pandemic.

In Fall 2021, the university required all student, faculty and staff to be vaccinated and wear masks when indoor or on buses. The 50% capacity limit, 15-minute single-trip limit, and social distancing requirement were subsequently lifted. Moreover, due to driver shortage, the buses could not continue to be run the same frequency designed in this paper, and we returned to normal bus routes used before the pandemic.

Conclusion

In this work, we redesigned the UM campus bus system to comply with social distancing guidelines by (i) limiting the route duration to at most 15 minutes, and (ii) only allowing 50% of the seats on a bus to be used. We consolidated bus stops to reduce the number of stops. We estimated demand for essential bus stops and O-D pairs, built an integer programming model to generate initial routes, and ran a simulation to evaluate the performance and resilience of the new design through stress tests. As it is essential to enforce social distancing to control virus spread during the pandemic, our approach can be utilized to quickly redesign public transit systems in different scales, for temporary or permanent use.

Acknowledgments

The authors are grateful for the support from University of Michigan (UM) Logistics, Transportation and Parking Department, for supplying data of the UM campus bus system. The authors also thank the College of Engineering at UM for administrative support to the team and financial support to all students who are involved in the research during Summer 2020.

References

Ahuja RK, Magnanti TL, Orlin JB (1993) *Network Flows: Theory, Algorithms, and Applications.* (Prentice Hall, Upper Saddle River, New Jersey).

Aykin T (1995) The hub location and routing problem. *European Journal of Operational Research* 83(1):200–219.

Campbell J, Ernst A, Krishnamoorthy M (2002) *Hub Location Problems* (Berlin, Springer).

Campbell JF, O'Kelly ME (2012) Twenty-five years of hub location research. *Transportation Science* 46(2):153–169.

Ceder A (2016) *Public transit planning and operation: Modeling, practice and behavior* (CRC press).

Chandrasekar P, Long Cheu R, Chin HC (2002) Simulation evaluation of route-based control of bus operations. *Journal of Transportation Engineering* 128(6):519–527.

Desaulniers G, Hickman MD (2007) Public transit. *Handbooks in operations research and management science* 14:69–127.

Dolen S, Denemy M, Shen S (2020) Conversation with the University of Michigan Campus Transit Operational Team.

Farahani RZ, Hekmatfar M, Arabani AB, Nikbakhsh E (2013) Hub location problems: A review of models, classification, solution techniques, and applications. *Computers & Industrial Engineering* 64(4):1096–1109.

Fonseca JP, van der Hurk E, Roberti R, Larsen A (2018) A matheuristic for transfer synchronization through integrated timetabling and vehicle scheduling. *Transportation Research Part B: Methodological* 109:128–149.

Guihaire V, Hao JK (2008) Transit network design and scheduling: A global review. *Transportation Research Part A: Policy and Practice* 42(10):1251–1273.

Ibarra-Rojas OJ, Delgado F, Giesen R, Muñoz JC (2015) Planning, operation, and control of bus transport systems: A literature review. *Transportation Research Part B: Methodological* 77:38–75.

Ibarra-Rojas OJ, Rios-Solis YA (2012) Synchronization of bus timetabling. *Transportation Research Part B: Methodological* 46(5):599–614.

Kim ME, Schonfeld P (2014) Integration of conventional and flexible bus services with timed transfers. *Transportation Research Part B: Methodological* 68:76–97.

Lopes MC, de Andrade CE, de Queiroz TA, Resende MG, Miyazawa FK (2016) Heuristics for a hub location-routing problem. *Networks* 68(1):54–90.

McCormick G (1976) Computability of global solutions to factorable nonconvex programs: Part i–convex underestimating problems. *Mathematical Programming* 10(1):147–175.

Michigan Engineering News (2020) The science behind campus bus changes during COVID-19. `https://news.engin.umich.edu/2020/08/the-science-behind-campus-bus-changes-during-covid-19/`.

Michigan News (2020) Safe busing during COVID-19: The science behind U-M's changes. `https://news.umich.edu/safe-busing-during-covid-19-the-science-behind-u-ms-changes/`.

Naumann M, Suhl L, Kramkowski S (2011) A stochastic programming approach for robust vehicle scheduling in public bus transport. *Procedia-Social and Behavioral Sciences* 20:826–835.

Ouyang Y, Nourbakhsh SM, Cassidy MJ (2014) Continuum approximation approach to bus network design under spatially heterogeneous demand. *Transportation Research Part B: Methodological* 68:333–344.

Rodríguez-Martín I, Salazar-González JJ, Yaman H (2014) A branch-and-cut algorithm for the hub location and routing problem. *Computers & Operations Research* 50:161–174.

U of Michigan Campus Transit (2020) University of Michigan Campus Bus Routes and Schedules. `https://ltp.umich.edu/campus-transit/routes-and-schedules/`.

Yan Y, Meng Q, Wang S, Guo X (2012) Robust optimization model of schedule design for a fixed bus route. *Transportation Research Part C: Emerging Technologies* 25:113–121.

Yang Z, Yu B, Cheng C (2007) A parallel ant colony algorithm for bus network optimization. *Computer-Aided Civil and Infrastructure Engineering* 22(1):44–55.

Yu B, Yang ZZ, Jin PH, Wu SH, Yao BZ (2012) Transit route network design-maximizing direct and transfer demand density. *Transportation Research Part C: Emerging Technologies* 22:58–75.

Zhang H, Cui H, Shi B (2019) A data-driven analysis for operational vehicle performance of public transport network. *IEEE Access* 7:96404–96413.

Zhang Z, Han T, Yoo KH, Capecelatro J, Boehman AL, Maki K (2021) Disease transmission through expiratory aerosols on an urban bus. *Physics of Fluids* 33(1):015116.

Appendix. Mathematical and Simulation Details

Integer Programming Model for Route Design We define notation and formulate an integer programming model for designing bus routes originating from and returning to each hub location as follows. Let I and J be the sets of potential bus-stop locations and routes that start and end in one of the hubs, respectively. For each route j in J, we denote K_j as the sequence of locations visited on the route. Our model aims to assign a bus-stop location from I (or a hub location) to each visit in K_j for each route j that is in use. Note that the number of bus stops on each route is not necessarily the same, and $|K|$ is set as the maximum number of visits allowed in any route and therefore we let $|K_j| = |K|,\ \forall j \in J$. In our computation, because the university requires that each route is less than 15 minutes and given the minimum travel time in between any pairs of bus stops in the campus bus system is 2.5 minutes, we set $|K| = 6$ in our model described later. If a route contains $k < |K|$, then the hub location repeats as the bus-stop location in the last $|K| - k$ stops.

Let c_j be the cost of operating route j for all $j \in J$. According to UM campus transit system operators, they normally hire a certain number of bus drivers (including back-up drivers) for each route created, and drivers' salary and benefits are the main part in the fixed cost c_j. Other parts in c_j include bus-stop setup and bus maintenance cost. We denote t_{i_1,i_2} as the average travel time from stop i_1 to stop i_2 for all $i_1,\ i_2 \in I \cup \{\text{hub}\}$, $\tilde{t}_{\text{stop}}$ as the average loading/unloading time at each stop. We assume that both t_{i_1,i_2} and $\tilde{t}_{\text{stop}}$ are deterministic and known. The assumption is validated by UM campus transit system operators based on their experience of operating campus buses in our university town.

We define binary variables $x_j,\ y_{ij},\ u^j_{i,k},\ u^j_{\text{hub},k} \in \{0,1\}$ for all $i \in I,\ j \in J,\ k \in K$ such that $x_j = 1$ if we operate route j, $y_{ij} = 1$ if we assign bus stop i to route j, $u^j_{i,k} = 1$ if bus stop i is the k^{th} visit in route j, and $u^j_{\text{hub},k} = 1$ if the hub is the k^{th} visited location in route j, respectively.

Using the defined parameters and variables, we first present the overall objective function of the optimization model as:

$$\min \sum_{j\in J} c_j x_j + \alpha \sum_{j\in J}\left(\sum_{i\in I} t_{\text{hub},i} u^j_{i,1} + \sum_{k=1}^{|K|-1} \sum_{i_1,i_2\in I\cup\{\text{hub}\}} t_{i_1,i_2} u^j_{i_1,k} u^j_{i_2,k+1} + \sum_{i\in I} t_{i,\text{hub}} u^j_{i,|K|} + \tilde{t}_{\text{stop}}\left(|K| - \sum_{k=1}^{|K|} u^j_{\text{hub},k}\right)\right), \tag{1}$$

where coefficient α is used as a weight to convert the total travel time and time spent on all stops into a related cost of operations and its value can be chosen based on gas price, operational frequency and other factors that will affect the operational cost. Note that the objective function uses a similar form in the facility location problem where there is a fixed cost associated with whether or not to operate a route and a continuous cost associated with the travel time of all routes. We use parameter α to adjust the emphasis on the two types of costs.

The objective function (1) involves bilinear terms $u^j_{i_1,k} u^j_{i_2,k+1}$, which we define by new variables $z^j_{i_1,i_2,k}$ and $z^j_{i_1,i_2,k} = u^j_{i_1,k} u^j_{i_2,k+1}$ can be linearized using McCormick envelopes (McCormick 1976):

$$z^j_{i_1,i_2,k} \le u^j_{i_1,k},\ \forall i_1, i_2 \in I \cup \{\text{hub}\},\ k = 1,\ldots,|K|-1,\ j \in J, \tag{2a}$$

$$z^j_{i_1,i_2,k} \le u^j_{i_2,k+1},\ \forall i_1, i_2 \in I \cup \{\text{hub}\},\ k = 1,\ldots,|K|-1,\ j \in J, \tag{2b}$$

$$z^j_{i_1,i_2,k} \ge u^j_{i_1,k} + u^j_{i_2,k+1} - 1,\ \forall i_1, i_2 \in I \cup \{\text{hub}\},\ k = 1,\ldots,|K|-1,\ j \in J. \tag{2c}$$

For each sub-region that contains one hub, the mixed-integer programming model for designing new routes is given by:

$$\min \quad \sum_{j\in J} c_j x_j + \alpha \sum_{j\in J}\left(\sum_{i\in I} t_{\text{hub},i} u^j_{i,1} + \sum_{k=1}^{|K|-1} \sum_{i_1,i_2\in I\cup\{\text{hub}\}} t_{i_1,i_2} z^j_{i_1,i_2,k} + \sum_{i\in I} t_{i,\text{hub}} u^j_{i,|K|} + \tilde{t}_{\text{stop}}\left(|K| - \sum_{k=1}^{|K|} u^j_{\text{hub},k}\right)\right) \tag{3a}$$

$$\text{s.t.} \quad y_{ij} \le x_j,\ \forall i \in I,\ j \in J, \tag{3b}$$

$$\sum_{k\in K} u^j_{i,k} = y_{ij},\ \forall i \in I,\ j \in J, \tag{3c}$$

$$\sum_{i\in I} u^j_{i,k+1} \le \sum_{i\in I} u^j_{i,k},\ \forall k = 1,\ldots,|K|-1,\ j \in J, \tag{3d}$$

$$\sum_{i\in I} u^j_{i,k} + u^j_{\text{hub},k} = x_j,\ \forall k \in K,\ j \in J, \tag{3e}$$

$$\sum_{i\in I} t_{\text{hub},i} u^j_{i,1} + \sum_{k=1}^{|K|-1} \sum_{i_1,i_2\in I\cup\{\text{hub}\}} t_{i_1,i_2} z^j_{i_1,i_2,k} + \sum_{i\in I} t_{i,\text{hub}} u^j_{i,K} + \tilde{t}_{\text{stop}}(|K| - \sum_{k=1}^{|K|} u^j_{\text{hub},k}) \le \mathcal{T},\ \forall j \in J, \tag{3f}$$

(2a)–(2c),

$$x_j \in \{0,1\},\ y_{ij} \in \{0,1\},\ u^j_{i,k},\ z^j_{i_1,i_2,k} \in \{0,1\},\ \forall i \in I,\ k \in K,\ j \in J. \tag{3g}$$

The objective function (3a) linearizes the original objective (1). Constraints (3b) allow bus stop i being assigned to route j if route j is in use; Constraints (3c) indicate that if a bus stop is in use (i.e., it is assigned to some route by having $y_{ij} = 1$), then it can be only assigned to one visit in the route. (Note that we do not necessarily need to assign a bus stop to a route and a bus stop can also belong to multiple routes.) Constraints (3d) prohibit assigning a bus stop to a visit in a route if an earlier visit has not been filled by any bus stop. Constraints (3e) indicate that for any visit in a route that does not have any bus stop being assigned to it (i.e., $\sum_{i\in I} u^j_{i,k} = 0$ at some k), the hub location is assigned to the visit (i.e., $u^j_{\text{hub},k} = 1$). (Note that together with Constraints (3d), if $u^j_{\text{hub},k^*} = 1$ starting from some visit k^* in a route j, then Constraints (3e) will enforce $u^j_{\text{hub},k} = 1$ for all visits $k > k^*$ on the same route. That is, the bus will be staying in the hub for the remaining visits $k^*, k^*+1, \ldots, |K|$.) Following the result of Constraints (3d) and (3e), we can use $|K| - \sum_{k=1}^{|K|} u^j_{\text{hub},k}$ to compute the actual number of bus stops in any route j. Therefore, the left-hand side of Constraints (3f) adds the total travel time and stop time on each route and the constraints enforce a time limit $\mathcal{T}$ (e.g., 15 minutes) for finishing each route.

Formulas for Bus Frequency Design Given T_j denoting the its estimated round-trip traveling time on route j, $1/f^{\text{old}}_j$ denoting the old bus system's busiest aggregated frequency passing through any stop in route j, we use the formula below to calculate the number of buses, n_j, needed on each new route j:

$$n_j = \left\lceil \frac{T_j}{f^{\text{old}}_j \times C} \right\rceil, \tag{4}$$

where we round up any fractional value to ensure that sufficient buses are assigned to each route, and the new bus frequency on route j is

$$1/f^{\text{new}}_j = \frac{n_j}{T_j} \text{ buses per hour.} \tag{5}$$

Algorithm 1 Main logic process in the simulation.

```
if Entity is Bus then
    if Location is UA then
        for Passenger on Bus do
            if GetOff(Passenger, currStop) = True then
                Unload Passenger
                Decrement currCap by 1
            end if
        end for
        Move To LA of currStop
    end if
    if Location is LA then
        for Passenger in WA of currStop do
            if GetOn(Passenger, currStop) = Route and currCap < maxCap then
                Load Passenger
                Increment currCap by 1
            end if
        end for
        Move To UA of the next Stop on Bus Route
    end if
end if
if Entity is Passenger then
    if Location is UA then
        stopID ← NextStop(Passenger, currStop)
        Exit If stopID = −1
        Move To WA of stopID If stopID ≥ 0
    end if
    if Location is WA then
        Move To LA If Load Requested and GetOn(Passenger, currStop) = Route
    end if
    if Location is LA then
        Loaded On Bus
    end if
end if
```

Algorithm 2 Functions used in the simulation to decide individual passengers' actions.

```
function Dijkstra(origin, dest):
Input: route graph, stopID origin, and stopID dest
Require: stop dest is accessible to stop origin
Output: the shortest path between the given stops: origin and dest
end function
function GetOn(Passenger, currStop):
Input: Passenger's attributes (origin and dest), stopID currStop that Passenger is currently at
Require: currStop is on the shortest path; Passenger is at WA
Output: Route that Passenger can take to move on the shortest path
end function
function GetOff(Passenger, currStop):
Input: Passenger's attributes (origin and dest), stopID currStop that Passenger is currently at
Require: currStop is on the shortest path; Passenger is on bus
Output: True if currStop is the destination stop or a transfer stop
end function
function NextStop(Passenger, currStop):
Input: Passenger's attributes (origin and dest), stopID currStop that Passenger is currently at
Require: currStop is on the shortest path; Passenger is at UA
Output: stopID of the next stop to wait; −1 (Exit) if currStop is the destination stop;
end function
```

Simulation Details Algorithm 1 describes the main logic of the simulation process and Algorithm 2 describes functions used for determining individual passengers' actions.

Tables 4, 5, 6, 7, 8 and 9 below show the bus stops on each new route, travel time from one stop to the next, and average bus stop time at each stop used in our simulation.

Table 4 Stops on route Campus Connector

Stop	Travel Time to Next Stop (min)	Avg. Bus Stop Time (min)
Pierpont - Bonisteel	1.7	2
Mitchell Field (Lot NC 78)	2.9	1
Glen and Catherine Inbound	2.2	1
Museum	0.9	2
Power Center	1.0	1
Glen and Catherine Outbound	2.9	1
Mitchell Field Lot M75	2.8	1
Cooley - Inbound	0.7	1
Pierpont - Bonisteel	–	–

Table 5 Stops on route Stadium-Diag Loop

Stop	Travel Time to Next Stop (min)	Avg. Bus Stop Time (min)
Oxford Housing	1.7	1
Stockwell	3.0	1
Mott Inbound	1.8	1
BSRB	1.5	1
Rackham	1.5	1
CCTC - Chemistry	1.7	2
East Quad	1.2	2
Henderson House	2.2	1
Oxford Housing	–	–

Table 6 Stops on route Oxford-Markley Loop

Stop	Travel Time to Next Stop (min)	Avg. Bus Stop Time (min)
Crisler Center Lot SC-7	2.0	1
Kipke and Green	1.8	1
IM Building Outbound	2.3	2
Law Quad	0.7	1
Michigan Union (NB State)	2.0	2
Kraus	1.3	1
CCTC - Chemistry	2.4	2
East Quad	2.5	2
Hill at Oakland	3.3	1
New Inbound IM	1.6	1
ICLE	5.2	1
Crisler Center Lot SC-7	–	–

Tables 10 and 11 below demonstrate the percentages of passengers for O-D pairs used in the simulation during 8am-10am and 12pm-2pm periods, respectively.

Tables 12 and 13 below show the bus stops passengers use for same-stop transfers or nearby transfers, and their corresponding routes.

Table 7 Stops on route Green Rd-NW5 Loop

Stop	Travel Time to Next Stop (min)	Avg. Bus Stop Time (min)
Green Road Park and Ride	3.6	2
Northwood 5	0.8	2
NCAC (on Hubbard)	0.7	1
Hubbard and Hayward - Inbound	1.1	1
FXB - Inbound	1.3	1
LMBE	2.1	1
Art and Architecture	2.3	2
FXB - Outbound	1.4	1
Hubbard and Hayward - Outbound	1.0	1
NCAC	1.9	1
Northwood 5	4.2	2
Green Road Park and Ride	–	–

Table 8 Stops on route Bursley-Baits Loop

Stop	Travel Time to Next Stop (min)	Avg. Bus Stop Time (min)
Pierpont-Murfin	2.3	2
Baits 2	0.8	2
Bursley	1.3	2
Northwood 1	1.9	1
Hubbard/Hayward Lot (NC46)	1.6	2
FXB Inbound	2.6	1
Pierpont-Murfin	–	–

Table 9 Stops on route Northwood Loop

Stop	Travel Time to Next Stop (min)	Avg. Bus Stop Time (min)
Pierpont - Murfin	1.3	2
Northwood 3	1.9	1
Northwood 2	1.7	2
Plymouth Road Crosswalk	1.1	2
Northwood Community Center	0.6	2
Hubbard/Hayward Lot (NC46)	3.4	2
Pierpont - Murfin	–	–

Table 10 Passenger arrivals during 8am-10am

Origin	Percentage (%)	Destination
Plymouth Road Crosswalk	7.08	Pierpont - Murfin
	1.92	Museum
Northwood Community Center	2.36	Pierpont - Murfin
	0.64	Museum
Northwood 2	2.36	Pierpont - Murfin
	0.64	Museum
Northwood 5	4.55	Art and Architecture
	2.45	Museum
Michigan Union (NB State)	14	Pierpont - Bonisteel
CCTC	19	Pierpont - Bonisteel
Baits 2	12	Museum
Bursley	8	Museum
IM Building Outbound	1.35	CCTC - Chemistry
	1.5	Pierpont - Murfin
Green Road Park and Ride	4.2	FXB Inbound
	2.8	Hubbard and Hayward - Inbound
Random	12	Random
Total	100	

Table 11 Passenger arrivals during 12pm-2pm

Origin	Percentage (%)	Destination
Pierpont - Murfin	7.08	Plymouth Road Crosswalk
	2.36	Northwood Community Center
	2.36	Northwood 2
	1.5	IM Building
Pierpont - Bonisteel	10	CCTC - Chemistry
	14	Michigan Union (NB State)
Art and Architecture	4.55	Northwood 5
CCTC - Chemistry	1.35	New Inbound IM
Museum	1.92	Plymouth Road Crosswalk
	0.64	Northwood Community Center
	0.64	Northwood 2
	2.45	Northwood 5
	12	Baits 2
	8	Bursley
FXB Outbound	4.2	Green Road Park and Ride
Hubbard and Hayward - Outbound	2.8	Green Road Park and Ride
Random	12	Random
Total	100	

Table 12 Stops where same-stop transfers are available

Stop	Route 1	Route 2
CCTC-Chemistry	Stadium-Diag Loop	Oxford-Markley Loop
East Quad	Stadium-Diag Loop	Oxford-Markley Loop
FXB Inbound	Bursley-Baits Loop	Green Rd-NW5 Loop
Pierpont - Murfin	Northwood Loop	Bursley-Baits Loop
Hubbard/Hayward Lot 46	Northwood Loop	Bursley-Baits Loop

Table 13 Stops that allow nearby-stop transfers

Location	Stops	Passing Routes
CCTC	Chemistry	Stadium-Diag Loop, Oxford-Markley Loop
	Museum	Campus Connector
FXB Building	Inbound	Green Rd-NW5 Loop
	Outbound	Green Rd-NW5 Loop
NCAC	Hubbard	Green Rd-NW5 Loop
	South Outbound	Green Rd-NW5 Loop
Pierpont	Bonisteel	Campus Connector
	Murfin	Bursley-Baits Loop, Northwood Loop
	Art & Architecture	Green Rd-NW5 Loop
Admin. Service	Kipke and Green	Stadium-Diag Loop
	ICLE	Stadium-Diag Loop
Mitchell Field	Lot NC - 78	Campus Connector
	Lot M - 75	Campus Connector
Glen and Catherine	Inbound	Campus Connector
	Outbound	Campus Connector
IM Building	New Inbound	Oxford-Markley Loop
	Outbound	Oxford-Markley Loop
Hubbard/Hayward	Lot NC - 46	Bursley-Baits Loop, Northwood Loop
	Inbound	Green Rd-NW5 Loop
	Outbound	Green Rd-NW5 Loop