CONNECTING U.S. CITIES VIA LOW-COST, HIGH-FREQUENCY, LONG-DISTANCE BUS SERVICES

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ABSTRACT

Long-distance (LD) inter-city bus service is an important transportation system option for most nations and many international travel settings. This study applies genetic algorithm optimization with an agent-based travel simulation model to optimize LD bus services and schedules for various crossUS applications. Optimal inter-city bus service performance is evaluated under different subsidy scenarios to identify useful policies for keeping LD travelers on the ground (where emissions and doorto-door travel costs are generally much lower than flying) while enabling inter-city access for all. The zero-subsidy/private-sector results align well with actual US LD bus operations, and routing optimization strategies suggest that just 761 50-seat buses driving 359,000 bus-miles per day (2,458 one-way bus-trips across 253 bus-routes) can serve about 100,000 US long-distance passenger-trips per day (fulfilling 75.7% of the nation’s daily bus-trip demand as estimated from RSG’s LD trip dataset and NHTS 2017) with 64.3% seat occupancy rate, and 36.3% profit margin, assuming $0.15-perpassenger-mile fares. Over 95% of those US long-distance passenger-trips are served directly, with just 3.4% of travelers needing to transfer (and transfers averaging 1 hour). The average bus-route (one-way) length is 146 miles, and the average passenger-trip is 108 miles (with a 71-mile standard deviation). Results also suggest that system subsidies of just $6M to $45M annually could lead to 4.6% to 17% higher bus-route frequencies and 2% to 14% more passengers served, while reducing CO_2 emissions by 17,000 to 144,000 tons annually, assuming those induced travelers are shifted from private vehicles. The simulation framework and findings can contribute to future analysis and policy implications of LD inter-city bus service.

Keywords: Long-distance travel, Inter-city busing, Bus service design problem, Agent-based simulation, Genetic algorithm

INTRODUCTION

Long-distance (LD) inter-city travel is a crucial component of transportation systems. It connects diverse geographic regions, enabling greater economic and social interaction and supporting tourism, transportation, and other industries. Despite comprising a small share of all travel, LD trips contribute significantly to traffic congestion, noise, crashes, and emissions. In the United States, LD person-trips (i.e., all those over 50 miles in one-way travel distance) were just 2.4% of all person-trips in the

2016/2017 National Household Travel Survey (NHTS) but contributed 43.2% of total person-miles traveled (PMT). In the UK, (Wadud et al., 2024) found that 2.7% of LD trips account for 61.3% of PMT and 69.3% of passenger travel's greenhouse gas (GHG) emissions. Despite the major role of LD and inter-city travel, there are relatively few LD-focused travel demand modeling efforts or LD bus-service investigations due to the infrequency of such trips, the extensive networks involved, the proprietary data details, and complex optimization heuristics needed to simulate and optimize such choice and service settings (Llorca et al., 2018).

Among LD travel mode alternatives, intercity bus service is among the most affordable, safe and accessible—yet sustainable and comfortable—options available, as compared to airlines, railways, and private automobiles (Javid et al., 2022). High-frequency buses can be especially attractive for trips under 300 miles, when flying has a minimal advantage in travel-time and relatively large costs and scheduling burdens. While railways may provide similar comfort benefits, bus services can provide broader route flexibility and better access, especially for underserved small towns and rural areas between major cities. In comparison to private automobiles, buses tend to offer Wi-Fi, reclining seats, mini-tables and restrooms, and they reduce the stress, dangers, and fatigue associated with long-distance driving. Additionally, buses generally have lower per capita emissions than private automobiles and airplanes, positioning bus travel as a crucial component of sustainable LD travel solutions (Bigazzi, 2019; Woldeamanuel, 2012).

While LD bus service provides an affordable trip fare and accessible and sustainable trip service, it undertakes substantial operational costs that cannot be completely recouped through fare revenues alone, particularly in regions with lower passenger densities. Meanwhile, it is vulnerable to economic fluctuations and policy changes. For instance, during the COVID-19 pandemic, a significant reduction in passenger numbers due to health concerns and travel restrictions policy led to a drastic drop in revenue for many bus service operator (Hirst et al., 2021). As a consequence, several regional bus operators, such as Megabus and Greyhound, scaled down and ceased their service or sold their assets to cover operational costs (Allard, 2023; News, 2024), which might further induce higher reliance on private automobiles for road travel (Abdullah et al., 2020).

Public transit subsidies are significant at the local or intra-regional level (averaging well 60¢ per passenger-mile in the US) (Litman, 2011), and transport supply decisions are common in urban planning and policymaking. Such subsidies lower travel costs for transit users, enable access for low-income households and many others, reduce reliance on private modes, free up parking space, and may lower roadway congestion. Zero-fare-transit policies within cities or urban regions are gaining interest (Kębłowski, 2020; Webster, 2024), and subsidies helped many systems survive COVID19 demanddrops (Dai et al., 2021; Ziedan et al., 2023). While benefits, costs, and operational strategies differ significantly between intra-city and inter-city bus systems, underlying principle that subsidies can help achieve broader socio-economic and environmental goals holds true. Exploring how these subsidies have been implemented and their outcomes in the LD inter-city bus context provides valuable insights for improving connectivity, affordability, and sustainability on a broader scale.

Keeping these factors in mind, this paper investigates how US inter-city bus service can perform more optimally (maximizing service while minimizing cost and route duplication), and how LD bus subsidies are likely to impact US system operations, access, and emissions. An LD inter-city bus network and service system was designed across 4486 National Use Microdata Areas (NUMAs) (approximately at county scale) in the contiguous 48 US states. Service frequency and system performance were determined using a joint simulation-optimization framework, with and without subsidies. The model design and paper results should be useful for national and international longdistance transit-system planning and decision making, for more demand-competitive, economically sustainable and environmentally friendly transportation systems.

LITERATURE REVIEW

This section synthesizes existing research on LD inter-city bus services, focusing on their evolution, societal and environmental impacts, and operational frameworks. It also examines transit planning models for optimizing service design.

LD inter-city bus service

Buses have been used between many US cities for over 100 years. Deregulation policy in the 1980s allowed US bus operators to freely enter and exit routes of their choosing, attracting investment from large-scale corporate interests and emerging service providers, such as Greyhound and Megabus. Expanding route options and the addition of power outlets plus Wi-Fi access have made LD inter-city bus service appealing to many travelers (Schwieterman, 2016), while increasing service and fare competition between providers, especially for the most popular city pairs (like routes between New York City and Boston). While LD inter-city bus routes exist mostly between two city or station pairs, many will stop along highways, to quickly drop off or add riders curbside (Schwieterman et al., 2012). Average US inter-city bus fares range from about \$0.08 to \$0.22 USD per passenger-mile (Schwieterman et al., 2019).

Greater demand for bus service can induce new routes and/or higher frequencies, thereby attracting more passengers (Liu et al., 2024). Affordability is an essential determinant of passengers' preference for it (Arbués et al., 2016; Dargay et al., 2012). It is found that the elasticity of US LD bus ridership in terms of fare is about -0.69 (Escañuela Romana et al., 2023). In central Europe, Tomeš et al. (2022) found that fare discounts and free fares program for long-distance public transport significantly increased ridership of railway and bus. Besides economic considerations, onboard comfort such as ample leg space and catering also makes buses an attractive LD travel option (Liu et al., 2024; Van Acker et al., 2020). Additionally, people of elderly age, with lower income, with disability, and those living in rural areas are found to rely more on inter-city buses for their essential mobility, which emphasizes the importance of LD inter-city buses in creating more equal and inclusive communities (Javid et al., 2022). The increase in LD bus ridership also contributes to carbon neutrality. It is estimated that carbon dioxide emissions from intercity buses are 50 grams per passenger mile, about one-fifth of automobiles and air (Bigazzi, 2019; Woldeamanuel, 2012).

Despite the promising social and environmental outcomes of the LD bus service, the current policy mostly leaves the business to survive itself, especially in a fully deregulated market, such as the US (Augustin et al., 2014), and limited attention has been paid to modeling the performance of the LD bus service and discussing the effect of subsidy on its performance. Therefore, a discussion of this problem may contribute to promoting the development of the LD inter-city bus for an inclusive and sustainable LD travel system.

Bus transit service planning problem

LD inter-city bus service can be regarded as a regional-scaled "urban bus transit service," where the whole country or a region is regarded as a "city" and cities of the country/region are treated as "bus stations". This conceptual framework allows for applying urban transit planning models to the planning and operation of inter-city bus services. Therefore, to simulate the performance improvement of emerging technologies in LD inter-city bus service, it is natural to design the service using the bus transit service planning model, which is extensively discussed in transit planning literature (IbarraRojas et al., 2015).

Planning a bus transit service is an optimization problem that involves several sub-problems, including network design, frequency setting, timetable development, bus scheduling, and driver scheduling (Guihaire et al., 2008). Typically, each sub-problem will be iterated multiple times to reach the final solution.

The network design problem (NDP) in bus transit planning is the most fundamental problem. It takes the physical road network and demand and distance matrices between origin and destination (OD) pairs as inputs to determine the most efficient configuration of routes and stops to maximize accessibility and coverage while minimizing costs and operational complexities. Given the excessive OD pairs and numerous combinations of intermediate stops between them, the NDP is a nondeterministic polynomial (NP) hard problem (Schöbel, 2012). Therefore, heuristic methods are proposed to provide near-optimal solutions. For example, line pool is a commonly adopted method where a set of potential routes is given.

Dargay et al. (2012) proposed a line pool generation approach, which allows the creation of pools with different properties to meet the objective function. Genetic algorithms are also frequently adopted. Szeto et al. (2011) proposed a genetic algorithm-based model to search all possible route structures instead of selecting routes from the predefined pool. For NDP, some constraints are often considered when determining solutions, such as fleet size, route length, route directness, and coverage (Yan et al., 2013).

While the NDP determines the general spatial profile of bus operation, the subsequent steps further implement the service into practical and actionable details, which highly requires a detailed temporal pattern of demands, buses, and drivers (Guihaire et al., 2008). Frequency setting determines the fleet size running on specific routes. A more frequent bus service can increase the passengers' perception of service level and trip demands but also lead to a higher operational cost. An ideal frequency setting can satisfy the trip demands with the least fleet size. Considering spatial and temporal varied demand elasticity in terms of frequency, Verbas et al. (2013) solved the frequency setting problem by maximizing the ridership and waiting time saving under the constraints of budget, fleet size, and vehicle capacity. Given the dynamic of traffic assignment, a Bi-level model is adopted, where the upper-level often optimizes the frequency, while the lower-level adjusts traffic assignment according to the frequency setting of the upper-level (Yu et al., 2010). Apart from deciding the bus departure time based on the frequency setting, the departure time can be directly determined by solving the timetable problem. In advance, solving the bus timetable problem allows the synchronization between different lines to increase passenger satisfaction (Ibarra-Rojas et al., 2012).

METHODOLOGY

Data source and preprocessing

The simulation of LD inter-city bus service relies on an understanding of LD bus demand between cities. In this study, the rJourney data, US national personal trip data, and NHTS 2017 data are synthesized to obtain the relatively latest nationwide LD travel demand at the fine county level. The rJourney data was created by the US Department of Transportation's Federal Highway Administration using a synthesized 31.5 million household population and cross-nested logit model (Perrine et al., 2020), which estimated the volume of round trips whose one-way distance is larger than 50 miles between any pair of 4486 NUMAs in 2010. The extent of NUMA is basically aligned with the county, but in the county with major cities, the county is further divided into multiple NUMAs (Fig. 1 shows the extent of study units). Data provides about 2.5 billion annual round passenger trips with four modes, i.e., private automobile, bus, rail, and air (Outwater et al., 2015). This study only considers the bus trips to represent the trip demand between a pair of NUMAs.

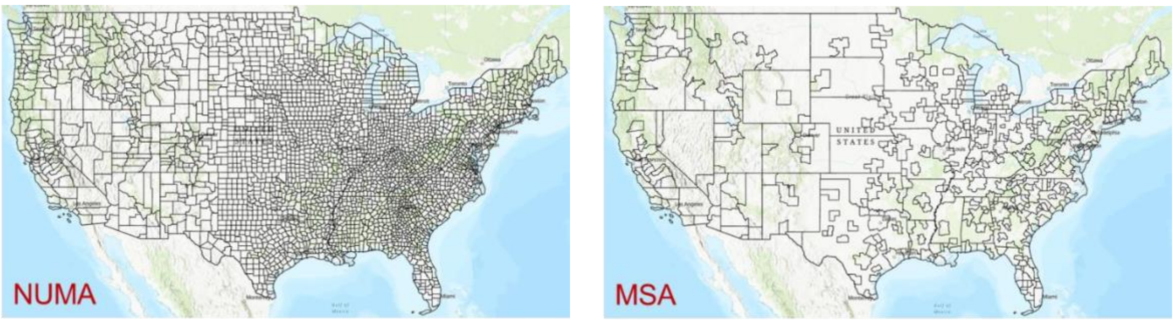


Fig. 1 Extent of study units of this study

To obtain a relatively latest demand, US national personal trip data is utilized to calibrate the 2010 bus demand matrix from rJourney. US national personal trip data provides the bus demand matrix between the Metropolitan Statistical Areas (MSAs), which spatially contains the extent of NUMA. Therefore, Eq. (1) is adopted, where $d_{i,j}^{2010}$ means the bus trip demand between NUMAs i and j in 2010, whereas $d_{i,j}^{2017}$ denotes the calibrated demand in 2017. $D_{I,J}^{2017}$ represents the bus trip demand between MSAs I and J. Here, $i \in I$ means MSA I spatially contains NUMA i.

D2017

$$d_{i,j} \quad = \quad \overline{\qquad\qquad} \quad d_{i2010,j} \quad * \textstyle\sum_{i\in I} \sum_{Ij,\in JJ} d_{i2010,j}$$

(1) 2017

The aforementioned bus demand contains bus trips from multiple submarkets, such as school buses, commuter bus, charter bus, tour bus, and city-to-city bus. Since the LD inter-city bus service simulated in this study is similar to city-to-city bus services such as Greyhound and Megabus, this study further calibrates the bus demand by Eq. (2), where N is the total volume of city-to-city bus demands obtained from NHTS 2017 data.

$$2017 * \underline{\qquad\qquad} N$$

(2)

$$d_{i,j} = d_{i,j} \qquad \textstyle\sum_i \sum_j d_{i2017,j}$$

Meanwhile, for a more realistic simulation result, an approximate LD trip departure time distribution is also acquired from the NHTS 2017 data, and the LD inter-city bus demand at a specific hour t is given by Eq. (3), where p_t is the probability of passenger planned departure time as shown in Fig. 2.

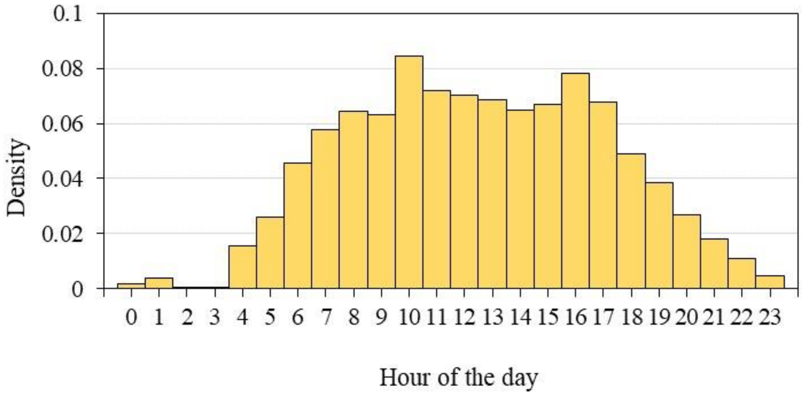


Fig. 2 Distribution of passenger departure time

$$d_{i,j,t} = d_{i,j} * p_t \tag{3}$$

Following trip demand extraction, this work prepares the bus stations by assuming that the LD inter-city bus service operates along the major highway, stopping at designated stations to connect cities. The specific location of the station is generated on the road network in each NUMA and each NUMA will only have one station.

For computational efficiency, three types of NUMA are ignored from the simulation. First, all US interstate highways and essential US highways and state highways are obtained to represent the road network. NUMAs that are not crossed by any road are ignored. Second, those detailed NUMAs that belong to one city are merged to reduce the redundancy of the station. Finally, the NUMAs with insufficient outbound and inbound demands are not considered. Based on the road network and generated stations, the distance matrix $Dist_{i,j}$ between stations is pre-calculated following the shortest path algorithm for later simulation.

Following the trip demand and station preparation, about 240 thousand daily one-way LD intercity bus demands are extracted. Fig. 3 presents the road network and projected LD inter-city bus demand on each road segment. In general, the LD inter-city bus demand is higher in the Eastern US, followed by Central and Pacific areas, and the demand is sparse in the Mountain area. The four bustlingly connected urban agglomerations include 1) Eastern agglomeration (Boston-New York CityPhiladelphia-Washington D.C.), 2) Central North agglomeration (Minneapolis-Milwaukee-Chicago), 3) Central South agglomeration (San Antonio-Austin-Dallas-Houston), and 4) Pacific agglomeration (San Francisco-Los Angeles-Las Vegas-San Diego). This spatial pattern is consistent with the result that

Schwieterman et al. (2019) obtained from real-world schedule data, demonstrating the reliability of demand extraction.

Fig. 3 Road network and projected LD inter-city bus demand

LD inter-city bus network design

This study utilizes the constraint-based line pool approach to design the LD inter-city bus network (Dargay et al., 2012). A valid bus route should meet four criteria including: 1) the length of a bus route should be less than 500 miles (range constraint) given the 8-hour maximum comfortable sedentary duration of passengers and safe driving duration of a single driver assuming the average speed at 60 mph; 2) the detour ratio of a route should be less than 1.1, as shown in Eq. (4), where $Dist_{i,j}^{r}$ is the route distance between the station of route i and j via route r; 3) the average distance between two stops should be no less than 50 miles to avoid frequent stopping (station interval constraint); and 4) demand between a route's start and end points (route origin and destination) should be no less than 15 persontrips per day, and total number of trips served by each route should be at least 25 trips per day (to eliminate low-demand routes, as a type of minimum-demand constraint).

$$\frac{Dist_{i,j}^{r}}{Dist_{i,j}} \leq 1.1 \quad for\ i, j \in r, i \neq j \tag{4}$$

Fig. 4 shows the flowchart for route pool generation. For a pair of stations i and j, an intermediate station k is not considered if the detour ratio via k is greater than 1.1 because this is the prerequisite that the detour ratio of the route containing k is less than 1.1. For all potential intermediate stations, a graph $G<E, V>$ is generated, where V is the set of origin, destination, and all intermediate stations, and E is the subset of the distance matrix. The depth-first search algorithm is applied to the graph to generate routes that depart at i and arrive at j via $\{k_1, \ldots, k_n\}$ that meet all criteria.

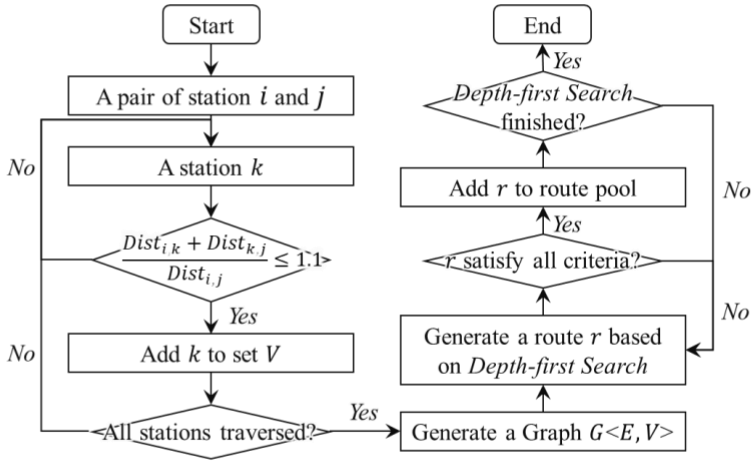


Fig. 4 Flowchart for route pool generation

Simulation framework

This study investigates the performance of the LD inter-city bus by simulating optimal route and timetable designs. Based on the extracted trip demand and generated route pool, an iterated framework consisting of an agent-based simulation model and genetic algorithm-based optimization is employed. The iteration will be terminated while the performance of the genetic algorithm converges or reaches the maximum iteration. Fig. 5 provides a general illustration of the simulation framework.

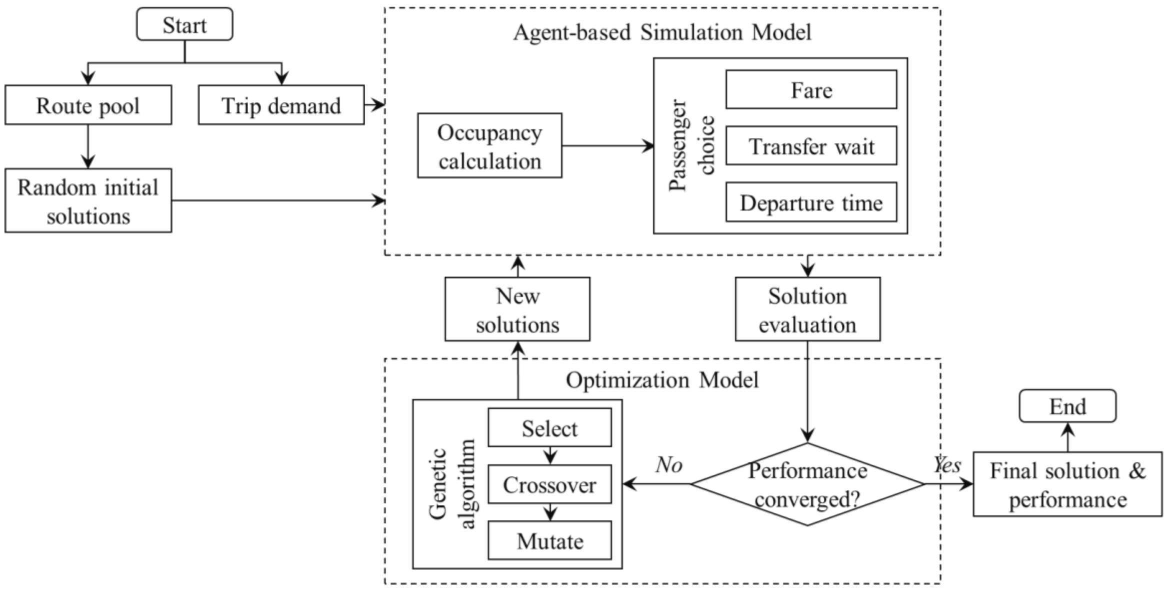


Fig. 5 Framework to simulate the LD inter-city bus service

Agent-based simulation

This study adopts agent-based simulation to model the selection process of passengers, whose definition and strategy are defined as follows.

Definition 1 (Trip) A trip T represents a passenger's LD inter-city bus demand containing the planned departure time T_t, the origin station T_o, the destination station T_d, and served status T_s. The passenger will prioritize the available bus(es) that departs closer to his planned departure time. However, it is assumed that any buses departing within the one-hour window to the planned departure time are indifferent. For example, given a trip departs at 6:00, buses depart at 5:00 and 6:59 are indifferent, while buses depart at 4:00 and 7:59 are indifferent. If a trip is finally served, T_s will be 1. While if no bus can serve the trip within a 3-hour departure window, the trip will be unserved and T_s will be 0.

For the buses that are indifferent in terms of departure time, the passenger is assumed to choose the one with the least trip cost regarding trip fare and time cost. In this study, the trip cost of a bus via the route r is computed as Eq. (5). f is the unit fare of the bus service, which is estimated as 15¢/mile according to the Greyhound online platform[1,2] and is consistent with prior findings (Schwieterman et al., 2019). VOT is the value of travel time and is determined as \$13.5/hour (Perrine et al., 2020). $Stop_{o^r,d}$ denotes the number of stops between the origin and destination stations via the route r. In this study, the average speed on the highway is estimated to be 60 mph and the stop time at each station is 5 minutes.

$$C_{o^r,d} = f * Dist_{o^r,d} + VOT * \left(\frac{Dist_{o^r,d}}{60} + \frac{5 * Stop_{o^r,d}}{60}\right) \quad (5)$$

For the trip cannot be served by a single bus, the passenger will further consider the transfer time into his trip cost as Eq. (6) where the function $trans(B_{ri}, B_{ri+1})$ calculates the transfer wait between the prior bus B_{ri} and subsequent bus B_{ri+1} operated on different routes. The maximum accepted transfer wait time is 2 hours.

$$C_{o\{r,d1,\ldots,rn\}} = \sum_{r\in\{r1,\ldots,rn\}} C_{or,d} + \sum_{i=1}^{n-1} VOT * trans(B_{ri}, B_{ri+1}) \quad (6)$$

Definition 2 (Bus) A bus B is represented by its route B_r and schedule B_s. The bus schedule represents the departure time of the bus at each traversed station, which is used to determine the passenger's choice together with the passenger's planned departure time. In this study, a bus has a capacity of 50 seats. The revenue and cost of a bus are represented by Eq. (7) and (8). For service revenue, 1/0.8 is an expansion factor given that the passenger fare revenue only accounts for about 80% of the total revenue, while the other includes delivery, food, and other service fees according to the disclosed financial report of Greyhound (FirstGroup, 2017) and governmental report (SEC, 2005). g is the comprehensive unit cost of the bus operation, including energy, tire, licensing, maintenance, labor, management, insurance, etc. In this study, the comprehensive unit cost of the bus is \$4.5/mile, synthesized and cross-validated by multiple sources (Lajunen et al., 2016; Lindly et al., 2015; Nookala et al., 1987).

$$revenue_B = \sum_{T\in B} \frac{f * Dist_{T^r{}_o,T_d}}{0.8} \quad (7)$$

$$cost_B = g * Dist^r \quad (8)$$

Genetic algorithm-based optimization

Based on the aforementioned simulation, the served status and net profit of the bus fleet are determined, and a genetic algorithm is utilized to optimize the number of bus fleet sizes and schedules. The objective function is presented by Eq. (9) to maximize the net profit of the bus trips as well as to serve more passenger trips. C is a negative constant acting as a punishment factor.

$$max \sum(revenue_B - cost_B) + C * \sum(1 - T_s) \quad (9)$$

Definition 3 (Solution) A solution S represents a designed bus service, including the route network, the fleet size of each route, and the schedule of each bus. It is the chromosome in the genetic algorithm where a gene demonstrates the service design of a route. Fig. 6 shows a schematic diagram of the chromosome and gene representation. $n \in N$, where N is the volume of the route pool. R_n is a gene on the chromosome, representing the timetable of all buses operated on this route. Specifically, it denotes a sequence of departure times for each bus at the origin station. With the departure time at the origin

[1] https://www.greyhound.com/
[2] All fare-related parameters in this study are presented in 2017 USD.

station, the schedule of a bus is determined. b is the size of the bus fleet on the route. If the length of a gene is 0, it means the route is not adopted in the designed LD inter-city bus service. For simplicity, this study assumes buses can depart in each half-hour.

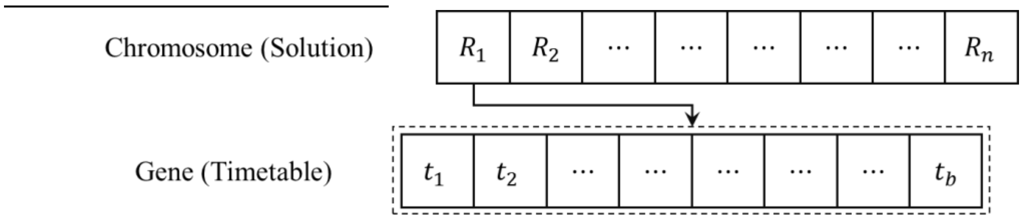


Fig. 6 Illustration of a solution

At the beginning of the framework, a population will be generated in which solutions of its members are randomly initialized. Each solution will execute the aforementioned simulation process to evaluate its performance. For the whole population, the select operator will choose the top 10% of solutions following the elite strategy and another 10% of solutions following the roulette strategy based on their objective function values to obtain the parents.

Subsequently, two parents are randomly picked to crossover to generate the remaining 80% of offspring as depicted in Fig. 7. The uniform crossover is applied so that each gene is decided whether or not to be swapped separately to introduce more offspring diversity.

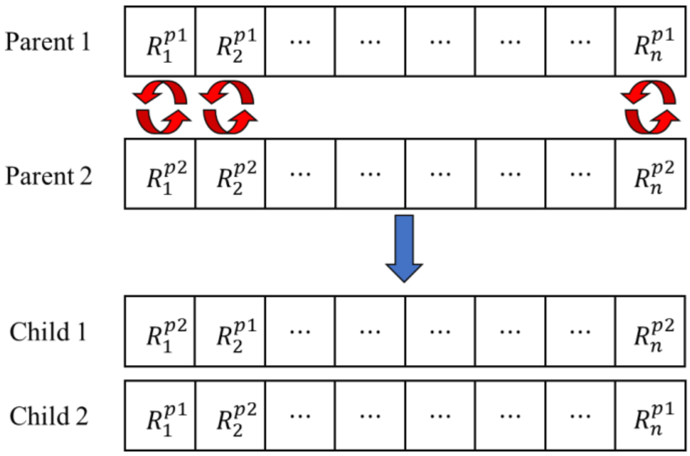


Fig. 7 Illustration of crossover

Finally, the mutate operator decides whether each of the departure times of a gene will mutate. Three types of mutation are considered including 1) replication: replicate the departure time, which means there will be one more bus that departs at the time; 2) deletion: remove the departure time, which means there will be one less bus that departs at the time; and 3) transformation: the current departure time will be transformed into another departure time. One of the mutate operators will be executed randomly in each run.

After all of the gene operators, parents, and all offspring will be fed into the simulation model for the next iteration until service performance converges or reaches the maximum iteration. The best solution for the last iteration is selected as the designed LD inter-city bus service and its performance will be analyzed.

Simulation scenarios

The objective of this study is to simulate the service performance of the LD inter-city bus service and understand the impact of operation subsidy. Therefore, scenarios are designed to reveal the impact. Table 1 summarizes the simulation scenarios of this study. In the baseline scenario, no subsidy is offered, which means the baseline and the current situation (Augustin et al., 2014). The daily trip demand is 128,568, which scales to 47 million annual long-distance person-trips by bus, and is aligned with Greyhound's 42 million person-trips-served number for its US bus operations (FirstGroup, 2017). It should be noticed that the daily trip demand listed here is the total demand for simulation that may not be entirely served.

Then, a subsidy is given to under-served OD pairs (where the served ratio is less than 50%) in the zero-subsidy scenario. Two subsidy recipient types (passenger versus operator) and 3 subsidy levels (5, 10, and 15 cents per passenger-mile traveled) are considered here. In the passenger subsidy scenario, the subsidy directly offsets the fare, which will increase trip demand, ceteris paribus. So trip demands are expanded according to a 69.47% fare elasticity assumption (Escañuela Romana et al., 2023). The maximum subsidy of 15¢/mile represents a zero-fare LD inter-city bus scenario since bus fares are approximately equal to 15¢/mile in the US on average.

In the operator subsidy scenario, the subsidy goes to the bus operator, allowing the operator to earn more money from any passenger it serves. For example, in the 15¢/mile scenario, the operator can earn 30¢/mile from the passenger traveling between the underserved stations. Although subsidizing the operator will not attract greater trip demands, it will make the bus not give up the route with limited profit, thus leading to the loss of public mobility for these passengers. However, it is worth noticing that the increase in trip demand due to a more frequent bus service is not considered for simulation simplicity.

Table 1 Simulation Scenario Details

Scenario	Subsidy amount	Subsidy recipients	Simulated daily person-trips
B (*Baseline*)	0	Not applicable	128,568
S5P (*5¢/mile Pax Subsidy*)	5¢/mile	Passenger	136,611
S10P (*10¢/mile Pax Subsidy*)	10¢/mile	Passenger	145,265
S15P (*15¢/mile Pax Subsidy*)	15¢/mile	Passenger	155,212
S5O (*5¢/mile Opr Subsidy*)	5¢/mile	Operator	128,568
S10O (*10¢/mile Opr Subsidy*)	10¢/mile	Operator	128,568
S15O (*15¢/mile Opr Subsidy*)	15¢/mile	Operator	128,568

RESULTS

Considering the complicity of bus service optimization, to avoid the influence of randomized initial solutions and increase the reliability of the result, each scenario is repeatedly conducted 20 times in this study. Taking the baseline scenario as an example, Fig. 8 presents the convergence process of the simulation framework. In this study, a maximum of 2500 iterations are adopted. The red and blue lines represent the highest and average objective function values of the solutions respectively, whereas the band depicts the result variation among repetitions. The objective function value improves significantly at the first 200 iterations and then grows slowly. The bottom right subgraph zooms into the boxed region and demonstrates a more detailed and clearer converged result. The simulation and optimization framework converge after 2000 generations. The final results only slightly vary among repetitions, indicating the effectiveness and stability of the simulation and optimization framework.

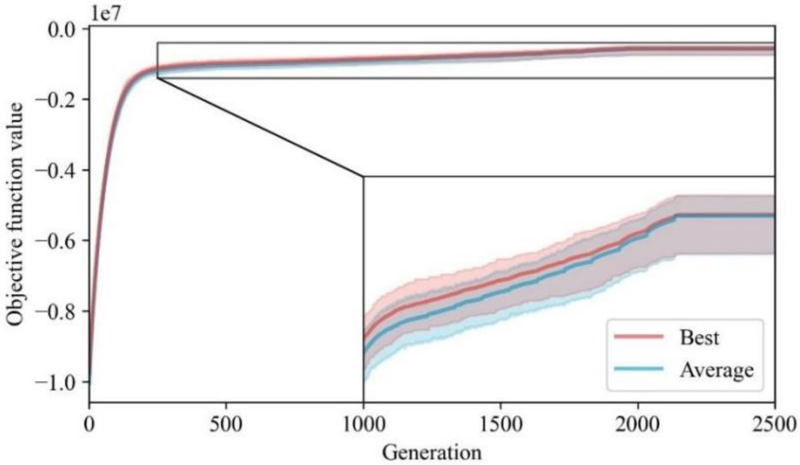


Fig. 8 Convergence process of simulation and optimization framework

Baseline LD inter-city bus performance

Table 2 summarizes the system performance of LD inter-city bus service under the zero-subsidy baseline scenario. The standard deviation shows that the simulation results are insensitive to the randomized solution initialization.

Table 2 Baseline LD inter-city bus service performance metrics

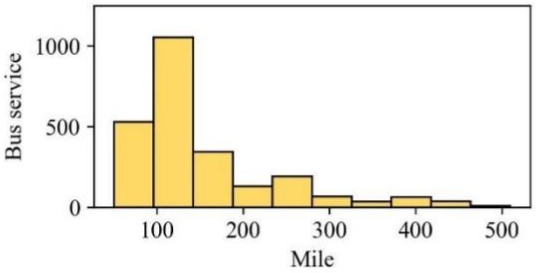
Category	Metrics	Mean	Std Dev
Passenger	Passenger-trip served per day	96,153 passenger-trips/day	1,818
	%Served trip demands	75.7% 3.31%	1.4
	%Trips with 1-transfer	0.06%	0.19
	%Trips with 2-transfer		0.02
	One transfer wait time	53.2 min	1.9
	Two transfer wait time	131.3 min	13.7
Vehicle	Passenger-trips per bus-trip	40.5 passenger-trips/bus-trip	0.5
	Load factor	64.3%	1.3
	VMT	146.3 mile/bus-trip	2.3
	Bus profit	$181/bus-trip	10.4
	Net profit per mile	$1.46/bus-mile	0.12
	Scheduled bus-trip per day	2,458 bus-trip/day	64
	Fleet size	761.1 vehicles	29.0

The number of passenger-trips served per day is over 75% of total US LD inter-city bus demand assembled here, and almost 100,000 person-trips per day. In a more bustling period, such as summer or holiday, the average passenger-trips served can be more. Among the served passenger-trips, over 95% are served via direct trips, with less than 3.4% of travelers needing to transfer between their origins and final destinations. Each transfer requires about 1 hour (53 minutes for 1-transfer travelers, and 131 minutes for the very few two-transfer travelers).

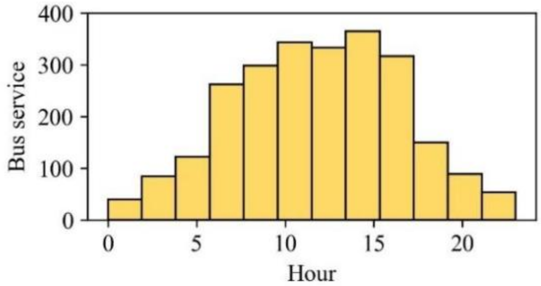
Making 2,458 scheduled bus-trip (from route endpoint to endpoint) departures a day, each bus-trip averages 41 served passengers, traveling roughly two-thirds full (since the 64% load factor equals system daily PMT divided by VMT). Each bus-trip nets an average of $181 in profit per bus-trip, or $1.46 per bus-mile. This totals to $162 million per year in profits (about $661 million in revenue and

$499 million in cost), which lines up well with U.S. Greyhound's $46 million annual profit and its 25% market penetration (FirstGroup, 2017). Roughly 761 buses are required to fulfill the operation, assuming a bus can be re-utilized for the return route after 1 hour when it finishes the main route.

Fig.9 shows the distributions of the bus-trip's route mile and departure time. It is found that most bus route lengths are less than 200 miles, basically covering the distance between major cities with bustling LD inter-city bus demands, such as New York City-Philadelphia, Los Angeles-San Diego, Dallas-Houston, and Milwaukee-Chicago observed in Fig. 3. The distribution of bus departure time is almost aligned to the departure time pattern of the passenger (Fig. 2) when most buses depart between 8:00 and 20:00.



(a) Route mile



(b) Departure time

Fig. 9 Distribution of LD inter-city bus service's route mile and departure time

The above simulated results of the baseline scenario almost align with the real-world performance, indicating the reliability of the simulation framework and providing confidence for the following analysis.

Service performances under subsidy

Table 3 lists the system performance of LD inter-city bus service under the different subsidy scenarios. Under both subsidy recipient and all subsidy amount scenarios, the service receives an improvement in the passenger-trips served, while the passenger-trips served increases as the subsidy grows. Fig. 10 demonstrates a clearer comparison of the passenger-trips served between the two schemes. When the subsidy amount is at 5¢/mile, the passenger-trips served are only slightly different between subsidizing passenger and operator. However, as the subsidy amount grows, there is a significant gap between the two schemes. While the passenger-trips served increases linearly in the subsidizing operator scheme, the subsidizing passenger scheme presents a nonlinearly increasing pattern, outperforming the subsidizing operator scheme, which can be due to the economics of scale of this service. Taking S15O and S15P as an example, the unit subsidy for one more served passenger is $14.7 and $8.9 respectively, indicating a higher efficiency of the subsidizing passenger scheme.

In terms of the served ratio, the subsidizing operator scheme can lead to consistent improvement. In contrast, although subsidizing passenger can serve more passengers, it cannot proportionally serve the induced demands. Therefore, its served ratio is found to decrease as the subsidy grows. For transfers, the transfer ratio sees a constant increase while the transfer time mostly drops slightly, which might be attributed to the increased scheduled bus-trips. For expenses on subsidy, the annual total subsidy is estimated to range from 6 to 45 million.

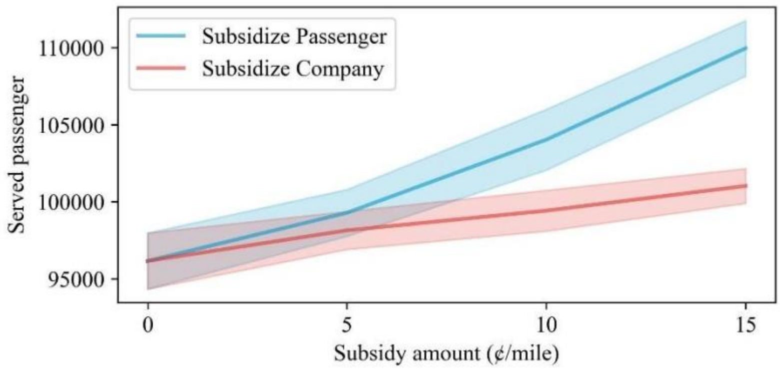


Fig. 10 Total served passenger under different subsidy scenarios

Regarding vehicle performance, since the vehicle is guided to serve those underserved passengers by subsidy, the passenger-trips per bus-trip and load factor both witnessed decreases, especially the subsidizing operator scheme, which allows the bus operator to still make profits with a lower load factor. The subsidy amount is also positively associated with the bus VMT, indicating that the LD inter-city bus is able to provide mobility and accessibility to a more distant area with the subsidies. For profitability, since the subsidizing operator scheme directly offers subsidies to the operator, the average net profit per bus-trip and per mile see huge growth. However, in the subsidizing passenger scheme, these two metrics both drop, indicating the operator may adopt a low margin, high volume strategy to optimally assign its fleet. In terms of scheduled bus-trips, subsidies can significantly lead to growth. Compared to the baseline scenario, there is a 4.6% to 17.4% rise in the number of bus-trips. Although the induced demand due to more frequent services is not considered in this study, it is reasonable to believe that there can be more demand after introducing a subsidy.

Table 3 Performance of LD inter-city bus service under different subsidy scenarios

Category	Metrics		Scenarios					
		B	S5O	S10O	S15O	S5P	S10P	S15P
Passenger	Passenger-trip served per day	96,153	98,139	99,416	101,022	99,280	104,020	109,950
	%Served trip demands	75.7 3.31	77.2 3.59	78.23	79.5 4.27	74.9	73.5	73.3
	%Trips with 1-transfer	0.06	0.08	3.89	0.12	3.99	4.31	4.68
	%Trips with 2-transfer			0.10		0.06	0.09	0.10
	One transfer wait time	53.2	53.3	52.9	53.1	52.5	52.5	52.5
	Two transfer wait time	131.3	128.7	129.9	130.2	136.2	124.5	127.8

	Total subsidy ($)	/	16,927	40,735	71,643	22,057	60,151	123,307
Vehicle	Passenger-trips per bus-trip	40.5	39.6	38.9	37.8	40.2	39.6	39.9
	Load factor	64.3	62.9	61.1	59.1	63.4	61.6	61.6
	VMT	146.3	148.3	152.5	155.0	149.8	153.1	157.6
	Bus profit	181	196.2	216.5	242.6	175.7	163.6	173.3
	Net profit per mile	1.46	1.48	1.51	1.55	1.37	1.21	1.20
	Scheduled bus-trip per day	2,458	2,570	2,658	2,792	2,574	2,746	2,885
	Fleet size	761.1	806.6	862.2	925.2	819.1	898.5	987.3

Sustainability and economic outcome of subsidy

Following the service performance analysis, this study further analyzes the sustainability and economic outcome of subsidies. Mature and professional road emission software COPERT is used to calculate the difference in carbon emissions due to the increase in the passenger-trip served, assuming passengers modeled in this study only choose between road transportation, i.e., private vehicles and LD inter-city buses. The private vehicle trip is assumed to follow the shortest path, and the average private vehicle trip distance is calculated to be 163 miles. Considering the average party size of a private vehicle trip is 2.15 persons and the carbon price is at $36/ton (Perrine et al., 2020), the estimated annually saved CO2, equivalent carbon price revenue, and the net subsidy after deducting the carbon price under each scenario is shown in Table 4.

Table 4 Carbon (CO_2) savings and subsidy results across scenarios

	Scenarios					
	S5O	S10O	S15O	S5P	S10P	S15P
Saved CO_2 (ton/ year)	17,596	24,752	34,967	31,005	79,610	144,263
Carbon price (million $/year)	0.63	0.89	1.26	1.12	2.87	5.19
Net subsidy (million $/ year)	5.55	13.98	24.89	6.93	19.09	39.81

The result reveals a positive correlation between the amount of subsidy and the amount of CO_2 saved, indicating that a higher subsidy can substantially enhance environmental outcomes. Since the subsidizing passenger scheme is assumed to attract a modal shift from private vehicles, there is a significant improvement in saved CO_2 over the subsidizing operator scheme, and the largest amount is about 144 thousand tons per year. The total amount saved is not quite significant due to two main reasons. Firstly, in this study, the subsidy is only provided to underserved areas. If the subsidy areas are expanded to a greater area, a more shocking result can be obtained. However, this is not realistic in terms of financial expenses. Second, the share of LD inter-city bus service in the US LD travel market is limited. Therefore, if the market is greater, we may receive a more promising outcome.

Based on the result, if the carbon trade policy is introduced, it may save $5 million a year under the S15P scenario, suggesting that environmental benefits can offset the subsidies. However, the share is limited and ranges from 5% to 14%.

CONCLUSION

LD inter-city bus service is an important component of the national LD transportation system. A developed and convenient inter-city bus service can help alleviate the reliance on private vehicle travel and provide necessary mobility and accessibility to less developed areas. However, its performance is seldom modeled. Currently, there is no well-provided route and timetable or passenger trip dataset of the service for analyzing its service performance. Therefore, this study proposed a joint simulation and optimization framework to simulate the performance of the LD inter-city bus service by solving the network and timetable design problem of the service.

Specifically, the genetic algorithm-based optimization algorithm and agent-based simulation are integrated to reveal the bus service performance. A specially designed representation has been proposed for representing bus travel frequency, timing, and routes in genetic algorithms. Based on the integration of multi-source real-world LD inter-city bus trip data, this study simulates the service performances under different subsidy scenarios to investigate the effect of financial subsidy on this service. With this data and simulation parameters obtained from the realistic official reports and articles, the simulation depicts its reliable ability to receive a stable optimization outcome and a realistic result that aligns with the real-world operation of the service, such as the Greyhound bus.

With the financial subsidy provided to underserved areas, we find that the LD inter-city bus service is able to provide more frequent services and serve more passengers. Basically, there is a scaling effect of the performance regarding the amount of subsidy. However, the recipient of the subsidy leads to different outcomes of service performance changes. In summary, subsidizing the bus operator enables them to provide service to areas that used to be with limited profitability. This can linearly improve the total served passengers and significantly increase the operator' profitability. In comparison, subsidizing the passengers can attract more passengers to adopt this service. Although the total amount of subsidy in the subsidizing passenger scheme is higher than the subsidizing operator scheme, it shows a nonlinear increasing pattern in the total served passengers and exhibits a higher efficiency in the marginal cost. However, the subsidizing passenger scheme will lead to slightly lower profitability even compared to the zero subsidy, which makes the operator serve more passengers with a lower margin. The environmental and economic outcomes of subsidies are further analyzed. It is found that subsidizing the LD inter-city bus service can receive a sustainable outcome in saving CO_2, and subsidizing the passenger helps to achieve a greater amount of saved CO_2. If the carbon price is introduced, it may help to slightly offset the subsidy expenses by about 10%. In real situations, service performance improvement, subsidy expense, and environmental outcome should be integrated to adopt a suitable subsidy scheme.

This study has certain limitations. For example, total LD bus-trip demand is taken as given for the US in 2017, irrespective of route travel times, and service frequencies (by the integrated system managers and by competitors, like airlines and passenger railways). Such a thoughtfully interlined system is likely to attract much higher demands than the 128,567 person-trips-per-day assumed here. Meanwhile, real demands vary by day of year, with certain months (like Spring and Summer months) and days of the week (like Friday) having much higher-than-average demands (Mori and Kockelman, 2024). Thoughtful fare and scheduling decisions can help keep buses and their operators/drivers busy, even during traditionally quiet times of the week and year. Taking a more holistic view of demand variations over time and space, and across competing carriers, with endogenous pricing and routing, will make for an interesting study. It would be useful to have more focused surveys of Americans to identify unmet demand and willingness to shift to such systems, thanks to more comfortable rides and more direct and faster service.

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