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The impact of congestion and dedicated lanes on on-demand multimodal transit systems

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ABSTRACT

Traffic congestion can have a detrimental effect on public transit systems, and understanding and mitigating these effects is of critical importance for effective public transportation. Implementing Dedicated Bus Lanes (DBLs) is a well-known intervention to achieve this goal. A DBL is a designated lane for bus transit, which avoids congestion and substantially lowers the travel time. This makes transit more attractive, encouraging more travelers to adopt public transportation. This paper studies the impact of congestion and DBLs on novel On-Demand Multimodal Transit Systems (ODMTS). ODMTS combine traditional rail and bus networks with on-demand shuttles. Previous case studies have shown that ODMTS may simultaneously improve travel time, reduce system cost, and attract new passengers. Those benefits were shown for an ideal world without traffic congestion, and this paper hypothesizes that the advantages of ODMTS can be even more pronounced in the real world. This paper explores this hypothesis by creating realistic congestion scenarios and solving bilevel optimization problems to design ODMTS under these scenarios. The impact of DBLs on ODMTS is evaluated with a comprehensive case study in the Metro Atlanta Area. The results show that DBLs can significantly improve travel times and are effective at increasing adoption of the system.

1. Introduction

Traffic congestion can have a detrimental effect on public transit systems, and understanding and mitigating these effects is of critical importance for effective public transportation. Implementing Dedicated Bus Lanes (DBLs) is a well-known intervention to achieve this goal. A DBL is a designated lane for bus transit, which avoids congestion and substantially lowers the travel time for riders. This makes transit more attractive, encouraging more travelers to adopt public transportation. Increased ridership in turn leads to a plethora of benefits, including fewer cars on the road, less emission, and increased revenue for transit operators that can be used to further improve service.

This paper studies the impact of congestion and DBLs on novel On-Demand Multimodal Transit Systems (ODMTS). ODMTS combine traditional rail and bus networks with on-demand shuttles (Van Hentenryck, 2019). Trains and buses serve the busy corridors on a fixed schedule, while shuttles dynamically serve the first and last miles. Fig. 1 provides an example of an ODMTS and the path of a single passenger. Passengers provide their origin and destination through a mobile application, after which the ODMTS provides a route to serve them. In this case, a passenger is picked up by an on-demand shuttle close to their origin and brought to the train station. The passenger is then instructed to take a train and a bus, which both run on a fixed schedule. When the passenger arrives at the bus station closest to the destination, another on-demand shuttle is ready to pick them up and serve the last mile. The Socially Aware Mobility Lab (2020) provides a video of this process.

Case studies in Canberra, Australia (Maheo et al., 2019), Ann Arbor, Michigan (Basciftci and Van Hentenryck, 2020, 2023; Auad and Van Hentenryck, 2022), and Atlanta, Georgia (Dalmeijer and Van Hentenryck (2020); Auad et al. (2021); Guan et al. (2022); Van Hentenryck et al. (2023)) demonstrate that ODMTS may simultaneously improve travel time, reduce system cost, and attract new passengers compared to the existing systems. Those benefits are shown for an ideal world without traffic congestion, and this paper hypothesizes that the advantages of ODMTS can be even more pronounced in the real world. By the very nature of ODMTS, shuttle trips are inherently local and minimally affected by traffic. Furthermore, buses are only used to serve high-density corridors, making DBLs for ODMTS potentially more impactful than for a traditional system.

A case study is conducted to fill the critical gap in understanding the

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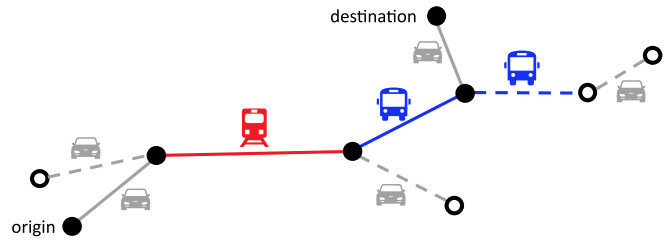


Fig. 1. Example ODMTS with Passenger Path (solid lines).

impact of congestion on ODMTS. Furthermore, it is shown that DBLs may lead to significantly increased rider adoption. The case study focuses on traffic from Gwinnett Country to the city of Atlanta, both in the Metro Atlanta Area (Georgia, USA). Gwinnett County is the second-most populated county in Georgia, with close to a million residents (U.S. Census Bureau, 2021). Many of these residents work in Atlanta and drive the Interstate 85 (I-85) for their commute, creating significant traffic. Fig. 2 summarizes Average Traffic Volume (ATV) from continuous count stations along I-85 (Georgia Department of Transportation, 2022). When driving south from Gwinnett to Atlanta, the ATV more than doubles on the highlighted section, which shows the importance of this highway and the high potential for congestion. Table 1 uses data from Google Maps to demonstrate the enormous potential of DBLs to reduce travel time on I-85. The table compares rush hour travel time to free flow travel time for both the full segment and for the highlighted segment. It can be seen that a DBL may save commuters from Gwinnett up to 61 min every morning.

Table 1
Travel Times and Potential Savings on I-85 (March 21–25, 2022).

	Full segment	Highlighted segment
Distance	28.8 miles	12.0 miles
Rush hour time (7am-9am)	28–85 min	12–50 min
Free flow time (2am)	24 min	10 min
Potential savings	4–61 min	2–40 min

The impact of DBLs is studied by creating different congestion scenarios and designing ODMTS with and without DBLs. Designing the optimal ODMTS is modeled as a bilevel optimization problem in which passengers choose whether to adopt the system based on the quality of the trip they are offered. This work combines the general model by Auad et al. (2021) with the adoption model by Basciftci and Van Hentenryck (2023). To solve this model at the scale of the case study, this paper applies the heuristic algorithm by Guan et al. (2022) and uses Benders decomposition to solve the fixed-demand ODMTS design problem in every iteration. This enables a comprehensive case study in the Metro Atlanta Area that considers different levels of congestion, shows the impact of DBLs, and demonstrates the increase in adoption of the ODMTS.

The contributions of the paper can be summarized as follows:

1. The paper creates realistic congestion scenarios and solves bilevel optimization problems to design ODMTS under these scenarios.
2. The paper evaluates the effect of congestion on ODMTS with a comprehensive case study in the Metro Atlanta Area.

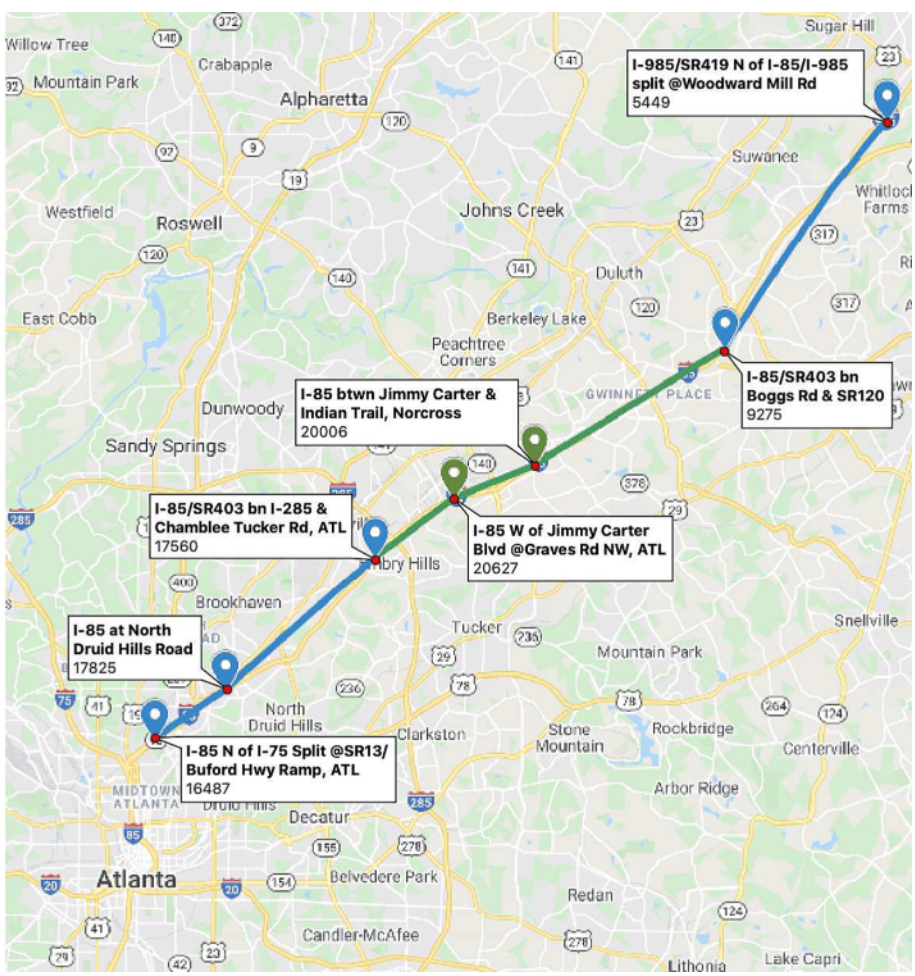


Fig. 2. Average Traffic Volume along I-85 during the 7am-9am Rush Hour (March 21–25, 2022).

3. The paper demonstrates on the case study that DBLs can significantly increase ODMTS adoption.

The remainder of this paper is structured as follows. Section 2 gives an overview of the literature. Section 3 presents the methods for generating congestion scenarios and designing ODMTS with and without DBLs. Section 4 introduces the case study area and the experimental settings. The effect of congestion on ODMTS without DBLs is analyzed in Section 5, after which Section 6 analyzes the effect of adding DBLs to the system. Section 7 concludes the study with final thoughts on DBLs in ODMTS.

2. Literature Review

DBLs have been studied through a variety of simulations and case studies. Basso et al. (2011) analyse a model where travelers have the choice between car, bus, and an outside option. The authors optimize frequency, vehicle size, spacing between stops, and capacity on DBLs to study different urban congestion management policies. It is found that implementing DBLs is a better stand-alone policy than subsidizing transit or pricing congestion. Russo et al. (2022) study the welfare effect of DBLs in Rome, Italy and conclude that DBLs may decrease bus travel time by 18%, decrease waiting time by 12%, and increase ridership by 26%. Furthermore, travel time for other motor vehicles may improve as well. Other case studies include the study by Ben-Dor et al. (2018) for Sioux Falls, South Dakota. The authors present an agent-based model and use the MATSim simulator to demonstrate that DBLs fundamentally improve the effectiveness of public transit and essentially make public transit trip durations similar during peak hours and non-peak hours. Hoonsiri et al. (2021) consider an intervention where fixed buses are allowed onto dedicated Bus Rapid Transit (BRT) lanes. A case study on the Rama 3 road in Bangkok, Thailand shows potential savings in travel time and a reduction in greenhouse gas emissions. Tsitsokas et al. (2021) formulate a nonlinear combinatorial optimization model to solve a DBL allocation problem on a large-scale road network. A case study in the San Francisco Metropolitan area demonstrates that the road network with DBL configurations significantly improves travel times for both cars and bus users compared to no DBLs.

Dedicated lanes have also been studied in the context of Autonomous Vehicles (AVs), where similar benefits are observed. Chakraborty et al. (2021) consider the problem of deciding which lanes on a freeway network should be AV-exclusive. Traveler choice between AVs and regular vehicles is captured by a logit model, and the resulting non-convex mixed-integer nonlinear program is solved through a combination of Benders decomposition and the Method of Successive Averages. The authors construct multiple freeway networks with up to 23 links to demonstrate the algorithm. Chen et al. (2020) explore the idea of giving AVs access to dedicated BRT lanes and focus on the interaction between AVs and BRTs. The authors first consider a model for mixed-use lanes, and propose a sequential optimization method to analyze the performance. The second model allows AVs to move in and out of the BRT lane at different locations, and is solved through successive linear programming. A case study for BRT Line 1 in Beijing, China shows that mixed-use lanes can both improve efficiency of AVs and reduce congestion on the other lanes.

The ODMTS concept was proposed by Maheo et al. (2019). They leverage ideas from hub arc location problems for transportation and telecommunication networks (Campbell et al., 2005) to design a hub and shuttle transit system that determines which bus arcs to open and how to serve the first/last miles with shuttles. A Benders decomposition algorithm is introduced to solve the problem, and a case study in Canberra, Australia demonstrates that the new system improves transit times without negatively affecting system costs. Auad et al. (2021) build on this work to present an end-to-end ODMTS solution that combines demand estimation, network design, fleet sizing, and real-time shuttle dispatching. Earlier methods are adapted to the multimodal setting, and practical constraints are introduced, such as a limit on the numbers of passenger transfers. The pipeline is used to conduct a case study in Atlanta, Georgia and to demonstrate the resiliency of ODMTS under various scenarios of COVID-19 pandemic response.

Recent studies on ODMTS have focused on including latent demand into the design of the network. Basciftci and Van Hentenryck (2020, 2023) study ODMTS Design with Adoptions (ODMTS-DA) with bilevel optimization models. The ODMTS-DA aims to design an ODMTS while taking into account that new passengers may adapt the system based on a personalized choice model. Exact methods are introduced to solve the ODMTS-DA, and a small-scale case study in Ann Arbor, Michigan demonstrates that ODMTS can improve service for the existing riders and attract new riders at the same time. Guan et al. (2022) develop heuristics to solve the ODMTS-DA for large-scale systems to which the exact method does not scale. These heuristics solve the problem iteratively by solving an ODMTS design problem with fixed demand, evaluating the passenger choices based on the new network, updating the ODMTS design problem, and repeating this process until convergence. A case study in Atlanta, Georgia is used to demonstrate that the heuristic is able to find high-quality solutions in significantly less time than the exact algorithm.

Other studies have investigated the coordination between on-demand services and public transit systems. Salazar et al. (2018) develop a network flow model and a pricing scheme to capture the interaction of Autonomous Mobility-on-Demand (AMoD) fleets with public transit. They undertake a case study on the existing transit system in New York City and show that integrating AMoD fleets with public transit brings significant benefits compared to AMoD fleets operating independently. Pinto et al. (2020) study the allocation of resources between transit systems and shared-use autonomous mobility services. They design a bilevel mathematical programming formulation that decides the balance between open bus routes and fleet sizes. Their case study in Chicago demonstrates significant benefits to passenger waiting times compared to the existing multimodal transit network.

The current paper studies whether the advantages of DBLs translate to ODMTS. Previous works on DBLs either study the effect of policy changes on existing systems or optimize how to modify existing systems. This paper leverages the fact that ODMTS is a novel type of transit system to introduce models that take congestion into account *while designing the system*. It also presents a case study for a large multi-modal system, while related optimization-based studies often focus on a single mode and a single corridor.

3. Methodology

This section introduces the methods that are needed to rigorously study the effect of congestion on ODMTS and to assess the benefit of DBLs. It first proposes an approach to model congestion in ODMTS with limited resources, and how to create the congestion scenarios that are used in the analysis. It then presents a bilevel optimization model to design ODMTS for these scenarios. It concludes by discussing how to incorporate DBLs into the design.

3.1. Congestion Modeling

Obtaining travel time predictions for various levels of congestion for each rider becomes computationally challenging or financially expensive for a large ridership. Therefore, this paper constructs congestion scenarios in two steps. The first step is to obtain a basis of travel times, and the second step is to multiply the travel time basis with a factor that depends on the congestion scenario and the local conditions.

Step 1: Travel Time Basis The travel time basis serves as the default travel time for any origin–destination pair (OD pair) in this study. For a given congestion scenario, the travel time basis is multiplied by a congestion scaling factor, resulting in the travel times under that scenario. The travel time basis is obtained from the POLARIS

Transportation System Simulation Tool (Auld et al., 2016). POLARIS is an agent-based modeling software tool created by Argonne National Laboratory that uses a dynamic simulation of travel demand, network supply, and network operations. It is used for a variety of cities to simulate an average day of activities, and has been tuned specifically for Atlanta using survey data from the Atlanta Regional Commission (Atlanta Regional Commission, 2022). POLARIS provides travel times between every pair of Traffic Analysis Zones (TAZs). The travel time between arbitrary points is approximated by the travel time between the corresponding TAZs. POLARIS *does* model congestion, but tuning to the survey data only provides a single scenario. This motivates the next step.

Step 2: Congestion Scaling Factors To determine an appropriate congestion scaling factor for every OD pair (without querying all of them), this paper introduces a set Q of Query Reference Locations (QRL). The set Q is shown by Fig. 3, and consists of existing Gwinnett bus stops, MARTA rail stations, and local points of interest in Gwinnett. For a given OD pair and a scenario k, the idea is to first identify the reference location $i \in Q$ closest to the origin and $j \in Q$ closest to the destination. The congestion scaling factor R_{ij}^k is then calculated as τ_{ij}^k/τ_{ij}^0, where the travel time τ_{ij}^k for scenario k is queried and τ_{ij}^0 is from the travel time basis in Step 1. The estimated travel time for the OD pair under scenario k is obtained by multiplying the OD travel time basis by R_{ij}^k. The benefit of this approach is that it allows for region-specific scaling but only queries travel times between the QRLs, which avoids prohibitively expensive data collection. In the case where $i = j$, i.e., the origin and the destination are mapped to the same QRL, the scaling factor is calculated between i and the QRL closest to i. (see Fig. 4).

Scenarios. The baseline scenario $k = 0$ is provided by the POLARIS travel time basis. To generate the congestion scenarios, this paper uses the Directions API on Google Maps Platform (2022) to obtain scaling factors for different levels of congestion. The Directions API supports two traffic models: `best_guess` and `pessimistic`, which approximate travel times under congestion. Based on these traffic models, three congestion scenarios are created:

- Expected: use `best_guess` travel times.
- 50–50: use the average of `best_guess` and `pessimistic` travel times.
- Pessimistic: use `pessimistic` travel times.

The corresponding travel times $\tau_{ij}^{exp}, \tau_{ij}^{50}$, and τ_{ij}^{pes} are queried between all $i,j \in Q$. Then the scaling factors $R_{ij}^{exp}, R_{ij}^{50}$, and R_{ij}^{pes} between all $i,j \in Q$ are calculated accordingly and define the scenarios.

3.2. ODMTS Design

This paper combines the general model by Auad et al. (2021) with the adoption model by Basciftci and Van Hentenryck (2023) to design an ODMTS that takes passenger adoption into account. The resulting bilevel model inherits support for transfer constraints, multiple frequencies, and both bus and rail connections. A full description is included below to clarify the assumptions and make the paper more self-contained. A more implicit description of a similar model can be found in Guan et al. (2022).

Problem Description. In the general model from Auad et al. (2021), the first input to the ODMTS network design problem is a transit network modeled by the directed multigraph $G = (V, A)$. Vertices V represent locations, and arcs $a \in A$ capture potential methods of transportation between these locations. Every arc from $i(a) \in V$ to $j(a) \in V$ is

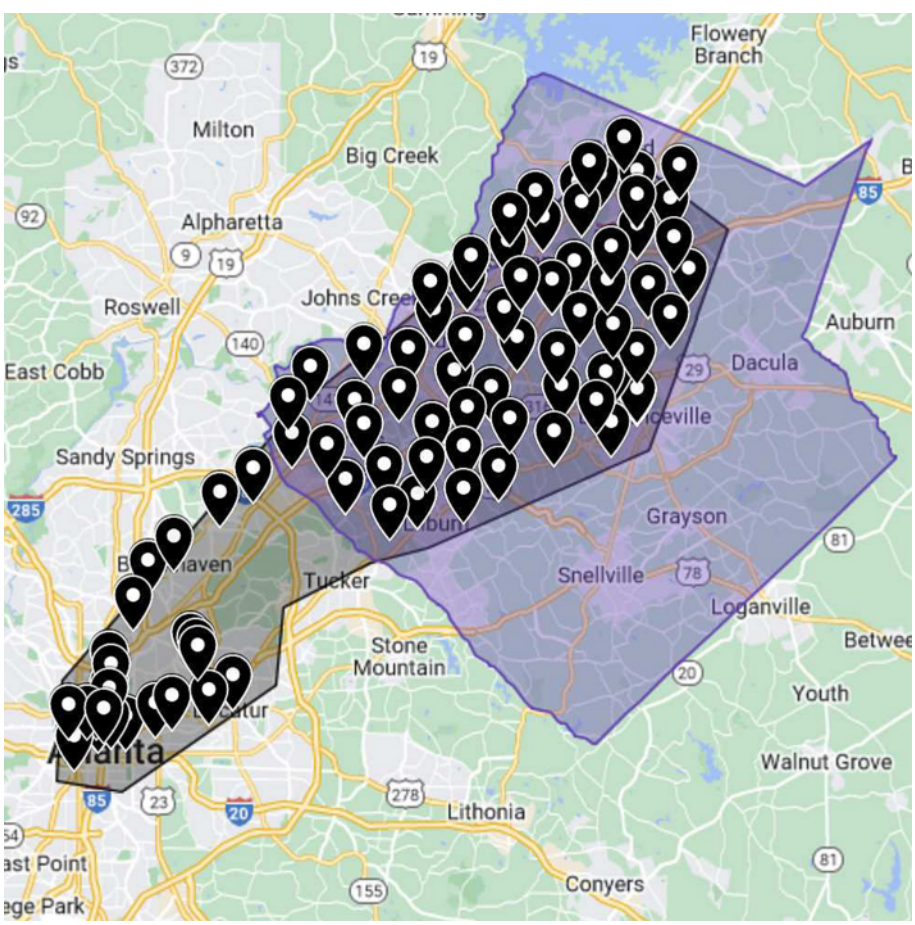


Fig. 3. Query Reference Locations with Respect to the Case Study Area (Gray) and Gwinnett County (Purple).

$$\min_{\boldsymbol{x},\boldsymbol{z}} \quad \sum_{a\in A^{bus}} \beta_a z_a + \sum_{t\in T\setminus T'} g^t + \sum_{t\in T'} x^t\left(g^t - \zeta^t\right), \tag{3a}$$

$$\text{s.t.} \quad \sum_{a\in\delta^+(i,bus)} f(a)z_a - \sum_{a\in\delta^-(i,bus)} f(a)z_a = 0 \qquad \forall i\in V_H, \tag{3b}$$

$$\sum_{a\in A^{bus}|i(a)=i,j(a)=j} z_a \le 1 \qquad \forall i,j\in V_H, \tag{3c}$$

$$x^t = \mathcal{C}^t(l^t) \qquad \forall t\in T', \tag{3d}$$

$$x^t \in \mathbb{B} \qquad \forall t\in T', \tag{3e}$$

$$z_a \in \mathbb{B} \qquad \forall a\in A^{bus}, \tag{3f}$$

where g^t and l^t are the optimal values to the follower problem:

$$\langle g^t, l^t\rangle = \operatorname*{lex\,min}_{\boldsymbol{y}^t} \left\langle \sum_{a\in A}\gamma_a^t y_a^t \ , \ \sum_{a\in A}(\tau_a+\omega_a)y_a^t \right\rangle, \tag{4a}$$

$$\text{s.t.} \quad \sum_{a\in\delta^+(i)} y_a^t - \sum_{a\in\delta^-(i)} y_a^t = \begin{cases} 1 & \text{if } i = o(t) \\ -1 & \text{if } i = d(t) \\ 0 & \text{else} \end{cases} \quad \forall i\in V, \tag{4b}$$

$$y_a^t \le z_a \qquad \forall a\in A^{bus}, \tag{4c}$$

$$\sum_{a\in A} y_a^t \le K, \tag{4d}$$

$$y_a^t \in \mathbb{B} \qquad \forall a\in A. \tag{4e}$$

Fig. 4. Bilevel Optimization Model for ODMTS Design with Adoptions.

associated with a mode $m(a)\in\{shuttle, bus, rail\}$ that indicates how this connection is served, and bus and rail arcs additionally have a frequency $f(a)$ from the set F^{bus} or F^{rail} respectively. Bus and rail arcs are used to transport riders between a set of transit hubs $V_H\subseteq V$, while shuttle arcs provide the connections to and from the hub network. For example, arc $a\in A$ may correspond to opening a bus connection with frequency 10 per hour between hub $i\in V_H$ and hub $j\in V_H$. It is important to note that G may have parallel arcs that model the same connection, but differ in mode or frequency. This is the case when a bus service can be offered at different frequencies, for example. The network design problem decides which potential arcs $a\in A$ to make available. In line with earlier work it is assumed that shuttle connections and the fixed rail network are always available, and the model only decides whether or not to open each bus arc (Auad et al., 2021; Guan et al., 2022). Furthermore, bus and rail capacities are ignored, as the high-frequency vehicles are almost never full in practice (Auad et al., 2021). Shuttle capacities are captured implicitly: the cost of using a shuttle represents the average cost for serving passengers in a ridesharing system with small vehicles. For convenience, the set of bus arcs is denoted by A^{bus}. Finally, every arc $a\in A$ is associated with a distance d_a, a travel time τ_a, and an expected waiting time ω_a. For shuttles and buses the travel time is based on the congestion scenario (as discussed in Section 3.1), while for rail the travel time approximates the current schedule.

The second input to the network design problem is a set T of passenger trips. Each trip $t\in T$ is an OD pair with origin $o(t)\in V$ and destination $d(t)\in V$, and is associated with $p(t)$ number of travelers. Capturing latent demand is essential when designing public transit services, as omitting these potential riders may cause inefficiencies and unfairness (Basciftci and Van Hentenryck, 2023). For this reason, the set T consists of both *potential riders* (i.e., latent demand) $T'\subseteq T$ who will only adopt the ODMTS if their travel time is sufficiently short, and *existing riders* $T\setminus T'$ who will always adopt the ODMTS. This study assumes existing riders have no alternative travel options, because they are already transit users. This behavior is captured by a choice function ^{t} that will be defined later. A trip that is served by the ODMTS is modeled as a path in G from $o(t)$ to $d(t)$. To prevent a large number of transfers, these paths are limited to at most $K\ge 1$ arcs.

The objective is to minimize a convex combination $\alpha\in[0,1]$ of system cost (weight $1\quad\alpha$) and passenger inconvenience (weight α) for the travelers who adopt the system. The fixed cost of opening bus arc $a\in A$ is defined as $\beta_a = (1\quad\alpha)\tau_a f(a)c^{bus}$, which combines the travel time τ_a, the number of buses over the time horizon $f(a)$, and the bus cost per hour c^{bus}. The rail network is assumed to be fixed, and the corresponding constant is omitted from the objective. Using arc $a\in A$ for trip $t\in T$ contributes to the objective as follows:

$$\gamma_a^t = \begin{cases} p(t)\ (1\quad\alpha)d_a\bar{c}^{shuttle} + \alpha\tau_a) & \text{if } m(a) = shuttle \\ p(t)\alpha(\tau_a+\omega_a) & \text{if } m(a)\in\{bus, rail\} \end{cases} \tag{1}$$

For shuttles, the distance d_a is multiplied by the shuttle cost per mile $\bar{c}^{shuttle}$, the inconvenience is the travel time τ_a, and the sum is multiplied by the number of passengers $p(t)$. For the other modes the only costs are fixed costs, such that γ_a^t only consists of the inconvenience $\tau_a+\omega_a$, which sums the travel time and the waiting time. For shuttles and buses, recall that τ_a is based on the congestion scenario. This means that opening bus arcs becomes more expensive, and using shuttles and buses becomes more inconvenient as congestion increases. Following earlier work it is assumed that shuttles are readily available and do not impose additional waiting time. This is motivated by the fact that shuttle waiting times are typically short (Van Hentenryck, 2019; Auad et al., 2021) and are comparable to the time it takes to park a car or walk to a bus station, which is not penalized either. For a given network design, passengers are always offered a route that minimizes the objective, but whether they accept this route and adopt the system depends on their personal preferences. If trip $t\in T$ is adopted, this additionally leads to a benefit of $\zeta^t = (1\quad\alpha)p(t)c^{ticket}$, i.e., the number of tickets multiplied by the price per ticket. Without loss of generality, the constant revenue from tickets sold to the existing riders is omitted from the objective.

Optimization Model. The bilevel optimization model by Basciftci and Van Hentenryck (2023) consists of the leader model (3) and a follower model (4) for every trip $t\in T$. For brevity, $\delta^+(i)$ denotes the set of arcs going out of $i\in V$, and $\delta^+(i,bus)$ further restricts this set to bus arcs. The sets $\delta\ (i)$ and $\delta\ (i,bus)$ are defined similarly for in-arcs. The leader model uses the binary variables z_a to decide which bus arcs $a\in A^{bus}$ are opened ($z_a = 1$) or closed ($z_a = 0$). Constraints (3b) ensure that the bus frequencies are balanced at every hub, and Constraints (3c) ensure that at most one frequency is selected among parallel bus arcs (recall that G is

a multigraph and may offer multiple frequency options for the same connection).

The leader anticipates the behavior of follower $t \in T$ through a binary variable x^t that represents the choice function $^t(l^t)$ (Eq. (3d)). The choice function equals one if $t \in T$ adopts, and zero otherwise. In particular, it is assumed that travelers adopt if they are offered a path of length l^t at most equal to the adoption factor ρ times the travel time by car l^t_{car}, i.e.,

$$^t(l^t) = \quad l^t \leqslant \rho l^t_{\text{car}}) \tag{2}$$

The leader Objective (3a) then sums the fixed cost for opening bus arcs, the cost and inconvenience for the existing riders, and the cost and inconvenience including ticket revenue for the potential riders that adopt ($x^t = 1$).

Based on the network design , the follower model (4) finds a path for trip $t \in T$ that minimizes the lexographic Objective (4a). The binary variables y^t_a for $a \in A$ define a unit flow from $o(t)$ to $d(t)$ that represents the path for this trip. Constraints (4b) enforce flow conservation, Constraints (4c) ensure that arcs can only be used if they are opened by the leader, and Constraint (4d) enforces the transfer limit. Followers are offered a path that minimizes the primary objective of cost and inconvenience, and ties are broken by minimizing the secondary objective of trip length. The corresponding optimal values are denoted by g^t and l^t respectively. Note that travelers decide whether to adopt based on the length of the trip l^t, while the leaders minimize a combination of trip lengths and cost.

Solution Method. Solving the bilevel model (3)–(4) is computationally challenging for large-scale instances. For this reason, this paper uses the iterative algorithm `arc-S2` by Guan et al. (2022) to approximate the optimal solution. This algorithm splits the original bilevel framework into two components: (i) a regular ODMTS network design problem without considering latent demand and (ii) a choice model to analyze the adoption behavior of the potential riders. The regular ODMTS network design problems are solved with the Benders-decomposition algorithm by Auad et al. (2021). After the initial design of the ODMTS, a subset of the bus arcs is permanently fixed in the optimization, the behavior of the potential riders is analyzed, and the active set of riders is updated. The ODMTS then undergoes a redesign based on the new set of riders, and this process is iterated until convergence. The output is an ODMTS network: It defines bus and rail connections and their frequencies, and it defines which areas are served by on-demand shuttles.

3.3. Including Dedicated Bus Lanes

It only remains to include DBLs into the ODMTS network design. Recall that the travel time for congestion scenario k is obtained by scaling the travel time basis with the appropriate congestion factor. For buses on DBLs, this travel time is simply replaced by the free-flow travel time, after which the same optimization methods can be used. The travel time basis is not necessarily the free-flow travel times: the baseline travel times are thus taken from OpenStreetMap (2021). It should be noted that the congestion scenario and the availability of DBLs are both inputs to the network design problem, such that the ODMTS delivers the best possible performance under these circumstances.

The approach to include DBLs in the network is flexible in the sense that any road or set of roads can be replaced with DBLs for analysis. The model is also not prescriptive in how the DBLs are realized, e.g., by using an existing lane or by adding a new lane. This paper focuses on the impact on the public transit system, but an interesting direction for future research could be to study the trade-off with car congestion when a regular lane is converted to a DBL. On the side of ODMTS, previous studies have shown that ODMTS generally reduce the total number of cars on the road (Auad et al., 2021; Van Hentenryck et al., 2023). Furthermore, increased traffic on the car lanes favors ODMTS, as the DBLs provide an even larger benefit.

4. Case Study Gwinnett and Atlanta

The case study in this paper focuses on Interstate 85 (I-85) from Gwinnett County to the city of Atlanta, both in the Metro Atlanta Area. The area is notorious for traffic, and Atlanta consistently ranks among the most congested cities in the US: After a temporary reduction in traffic during the COVID-19 pandemic, the city has jumped back to the 10th place on the list in 2021 (Pishue, 2021). Gwinnett County has almost a million residents, many of which work in Atlanta and drive the I-85 for their commute. Gwinnett County recognizes the integral role of transit in the transportation system and published a transit development plan in 2018 (Gwinnett County, 2018). In 2019, Gwinnett County and the Georgia Department of Transportation (GDOT) presented a study of I-85 traffic and strategies to alleviate the extreme congestion (Wickert, 2020). However, the Atlanta Journal Constitution reports that Gwinnett County and GDOT officials are still seeking solutions to reduce congestion on I-85 (Wickert, 2021). This highly congested area serves as an excellent case to study the extent to which DBLs can improve passenger adoption in ODMTS. Fig. 5 visualizes the case study area and its relation to Gwinnett County. The area is specifically chosen to encompass I-85 and the immediate surrounding areas, and includes the current commuter routes operated by Gwinnett County Transit. The markers represent strategic locations that will be used as potential hubs to design the ODMTS. To clearly demonstrate the effect of congestion, the case study focuses on the morning rush hour from 7am to 9am and the associated southbound traffic from Gwinnett to Atlanta.

Current System. The bus transit system in Gwinnett County is operated by Gwinnett County Transit (GCT). GCT operates seven local bus routes within Gwinnett County and five commuter routes that connect to DeKalb County (Emory University) and Fulton County (Midtown Atlanta and Downtown Atlanta). The commuter routes are shown by Fig. 6, and it can be seen that all routes use the I-85. In Atlanta, the buses stop at destinations in Emory University, Midtown, and Downtown: they connect to the MARTA transit system that is operated by the Metropolitan Atlanta Rapid Transit Authority (MARTA), e.g., at the Civic Center station. Where available, transit vehicles make use of High Occupancy Toll (HOT) lanes on the I-85 (Georgia Department of Public Safety, 2022). These lanes are shared with three or more person carpools and with drivers who pay toll, among other traffic. To isolate the effect of DBLs, this study compares the situation without HOT lanes to a new situation where the extra lane is dedicated to buses only.

Existing Ridership. This paper uses real transit data to generate a realistic set of trips that represents the existing ridership. Historical ridership is obtained from the Automated Fare Collection (AFC) system of GCT. Riders use a transit card known as the *Breeze Card* to tap onto the buses. For every tap, the AFC system records card id, time of transaction, type of transaction, and which reader was tapped. This information is combined with the Automated Vehicle Location (AVL) system that tracks the buses, and the Automated Passenger Counter (APC) system that counts boardings and alightings at every stop. Data was collected for the 7am-9am morning peak for April 16–19, 2018. Trip chaining techniques from Barry et al. (2002) are used to estimate OD pairs. Finally, the trips are sampled from the dataset to obtain a set of 898 passengers that represent the existing ridership. Together these passengers generate 648 unique OD pairs. The GCT transit data is the most representative and fine-grained data available for the existing ridership, but it does not track riders beyond their current boarding and alighting stops. Existing riders may therefore see an additional improvement if they switch to ODMTS for their full door-to-door commute, eliminating the time it takes to get to and from the current transit stops.

Potential Riders. In addition to existing riders, a set of potential riders is generated: they may choose to adopt the system if the travel time is sufficiently short. The set of potential riders is based on simulated travelers in the Metro Atlanta Area provided by the Atlanta Regional

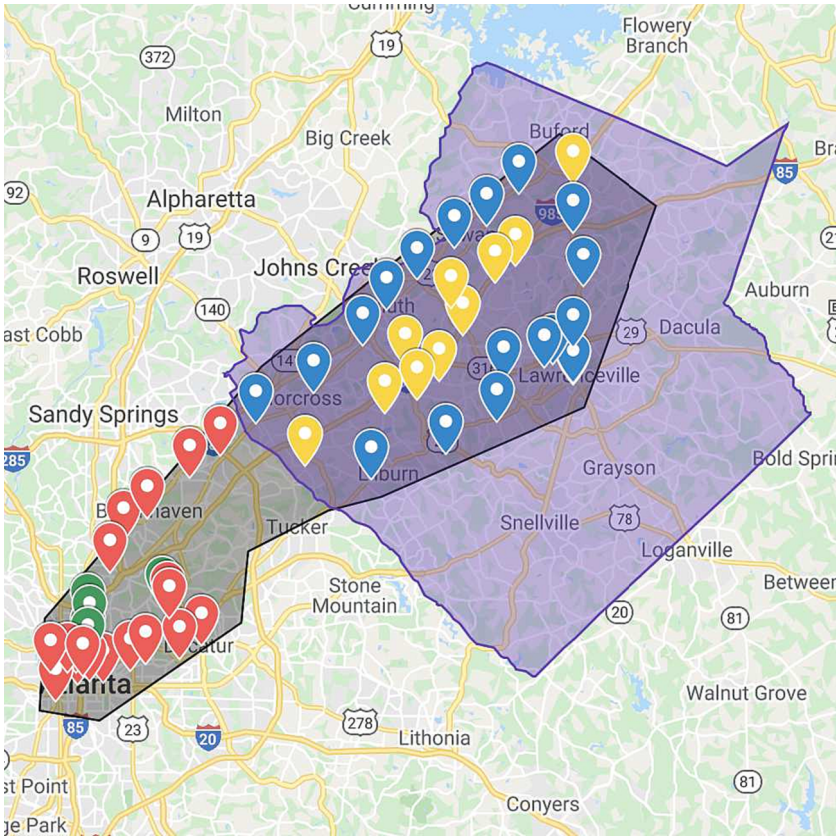


Fig. 5. Case Study Area (Gray), Gwinnett County (Purple), and Potential Hub Locations (Markers).

Commission (2022). This data was generated by an activity-based model, calibrated with data from the 2011 Regional Houshold Travel Survey, and projected into 2020. This dataset does not include the impact of the COVID-19 pandemic, but Auad et al. (2021) have demonstrated that ODMTS are generally resilient to changes in demand. To create a set of potential transit users, travelers are selected from those who

- commute alone by car from Gwinnett County;
- depart during the 7am-9am morning peak and stay within the case study area; and
- commute to the Emory University area, Midtown Atlanta, Downtown Atlanta, or stay within Gwinnett.

This results in 33,769 potential riders: 31,295 local riders (who commute within Gwinnett) and 2,474 non-local riders who work outside of the county. The trip origins, which are provided at the level of traffic analysis zones, are distributed over smaller census blocks based on population counts. Similarly, the trip destinations are distributed over points of interest based on size, resulting in 27,202 unique OD pairs. Note that potential ridership is based on simulated demand from the survey, while existing ridership is based on the current actual demand.

Experimental Settings. The congestion scenarios are created according to Section 3.1, using Directions API data for 8am on Wednesday March 22, 2022. The MARTA rail system is fixed, while the GCT buses are redesigned. The ODMTS provides service to 1733 conveniently-placed *virtual stops* that span the case study area (chosen from existing transit stops, census block centers, and points of interest), and the OD pairs are mapped to nearby virtual stops. Fig. 5 shows the potential hub locations that are used for the case study. These include hubs near I-85 (yellow), hubs in Gwinnett (blue), MARTA rail stations (red), and hubs at or near current GCT commuter bus stops in Atlanta (green).

Table 2 shows the parameter values used for the ODMTS design, with α, c^{bus} and $\overline{c}^{shuttle}$ taken from Auad et al. (2021). The bus cost of $72.15 per hour is based on data from Federal Transit Administration (2018) and Dickens (2020) and consists of salaries and wages ($39.55 per hour), maintenance ($19.17 per hour), and vehicle depreciation ($13.43 per hour). The shuttle cost per mile is the estimated total cost to serve passengers with a real-time ride-sharing system. The suggested shuttle cost per mile is multiplied by the congestion factor to capture the increase in cost due to traffic. Ticket prices are set to follow GCT. Buses are added at a frequency of 10 buses per hour to maintain the notion of high-frequency connections. It is worth noting that because buses only serve the busy corridors, ODMTS can operate them at higher frequencies compared to typical routes. Auad et al. (2021) do not explicitly model bus lines, and assume that every arc corresponds to a transfer that induces wait time. As bus lines from Gwinnett to Atlanta play an important role, this paper removes the limit on how many arcs riders can use ($K = \infty$) and adds waiting times in a post-processing step, rather than at every stop. Waiting for a bus or train is assumed to be five minutes, which is a conservative estimate based on the three-minute expected waiting time and a two-minute buffer for transfers or to get into a station. Shuttles are assumed to be readily available, as discussed in Section 3.2. The set of adopting riders is updated accordingly in post-processing.

The ODMTS network design problem with adoptions is solved with the iterative algorithm `arc-S2` by Guan et al. (2022), which is implemented in Python 3.7. In every iteration, the algorithm calls the Benders-decomposition algorithm by Auad et al. (2021) to solve an ODMTS network design problem for fixed demand. The Benders-decomposition algorithm is implemented in C++ and uses CPLEX 12.9 to solve (mixed-integer) linear programs.

5. Impact of Congestion on ODMTS

This section studies the impact of congestion on ODMTS. For each of the congestion scenarios, an ODMTS is designed to deliver optimal

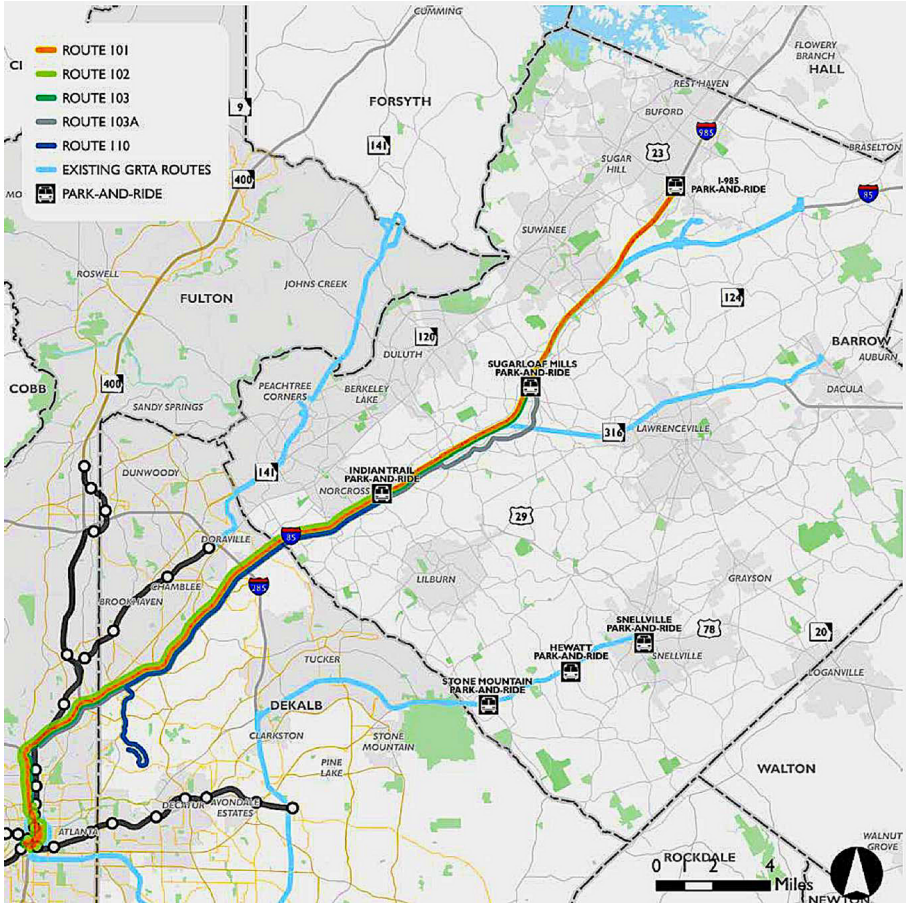


Fig. 6. GCT Express Routes.

Table 2
ODMTS Parameters for Case Study.

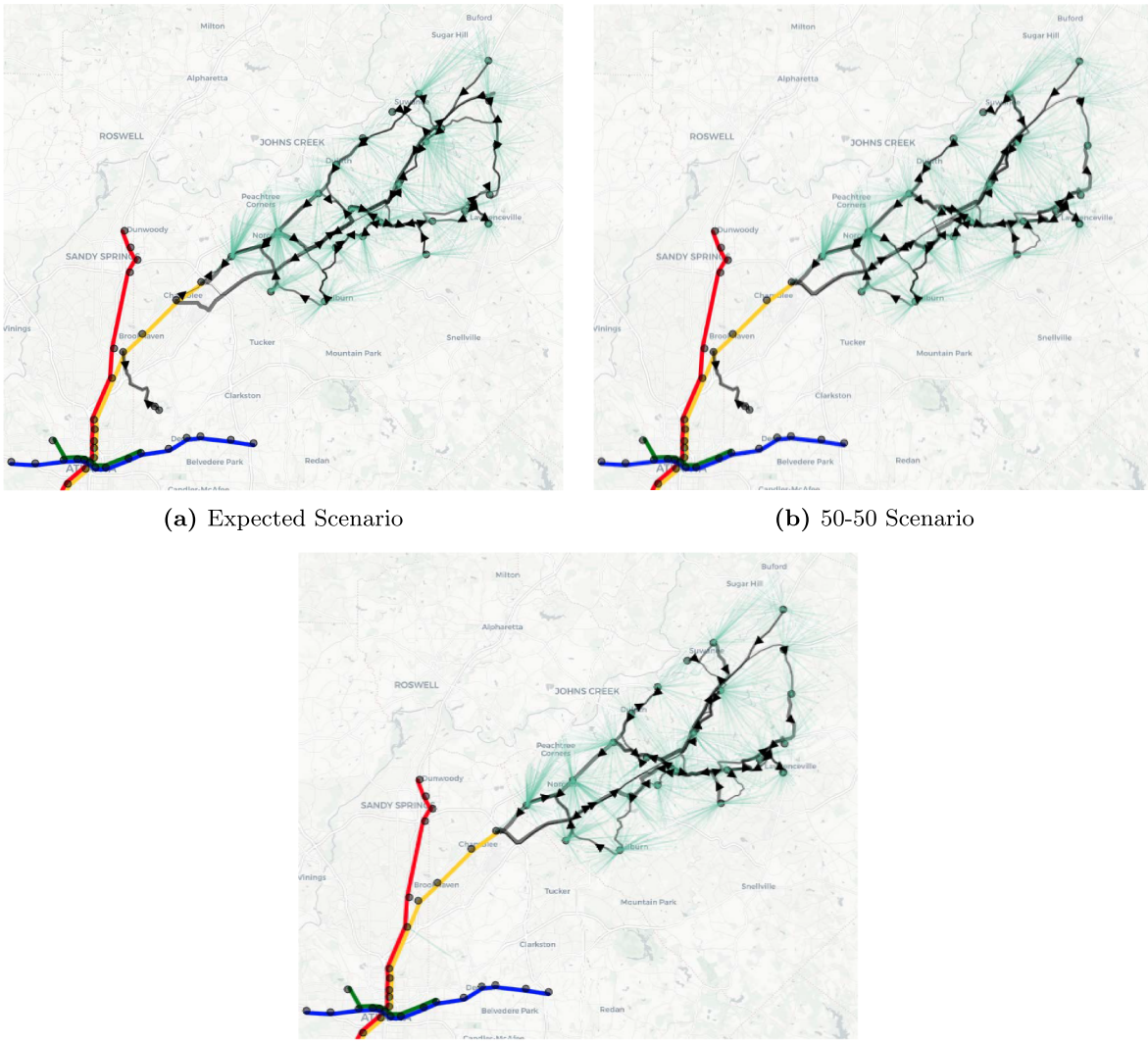
Parameter	Value
α	0 1078 (value time at $7.25/hour to match U.S. federal minimum wage).
c^{bus}	$72.15 per hour.
$\bar{c}^{shuttle}$	Basis of $1/mile multiplied by congestion scaling factor.
c^{ticket}	$3.50/trip for local and $5/trip for non-local.
F^{bus}	{10} buses/hour.
K	∞ (no transfer limit).
ρ	1.5 adoption factor.

performance in that scenario, and it is analyzed how these systems differ in service quality and cost. This analysis also serves as the baseline for studying the impact of DBLs in Section 6.

Network Designs. Fig. 7 presents the ODMTS network designs, optimized under the different congestion scenarios. The lines in the Southwest represent the Red, Gold, Blue, and Green lines of the MARTA rail system. The lines with arrows (gray) show the bus arcs that are opened by the optimization model, where the thickness of the line corresponds to the number of travelers that use this arc. Finally, the thin lines (green) indicate which connections are served by on-demand shuttles. It is striking that none of the designs feature a bus connection on the I-85 from Gwinnett to Atlanta. This corridor is so congested that the ODMTS transfers passengers to rail at Chamblee and Doraville stations rather than provide a direct bus connection to the city. In the expected and 50–50 scenarios, there is a bus service that connects the rail to Emory University. Under the pessimistic scenario, this bus also disappears in favor of serving a small number of people by shuttles. The overall designs look similar for the different scenarios, but the ODMTS increases its reliance on shuttles as congestion increases: the total shuttle distance increases from 62k miles for the expected scenario, to 66k miles for the 50–50 scenario, and 72k miles for the pessimistic scenario.

Travel Time and Adoption. Fig. 8 zooms in on the travel time and adoption of non-local travelers, who are most likely to be affected by congestion. Congestion has a major effect on the existing riders: travel time increases from 64 min under the expected scenario to 86 min under the pessimistic scenario. While the number of existing riders is fixed, potential riders adopt the ODMTS if the travel time is not too long compared to driving. Surprisingly, Fig. 8 shows an increase in adoption when congestion increases, despite the increase in travel time. This is due to the fact that travel time by car is also negatively impacted, making transit a more favorable option. There is 52% adoption of potential non-local riders under the expected scenario (1279 people), which increases to 72% under the pessimistic scenario (1770 people). Local riders are less affected by congestion, but show similar trends. Travel time for existing riders increases from 23 min under the expected scenario to 33 min under the pessimistic scenario, while the adoption rate increases from 61% to 66% of the potential riders (from 19,013 to 20,646 riders). The high adoption rates suggest that ODMTS may significantly improve access to transit and may compete with commuting by car for a variety of congestion levels.

Congestion. To get a better understanding of how congestion affects system operations, Fig. 10 displays the scaling factors for the roads used by the ODMTS. For the expected scenario (Fig. 10a) the average scaling factors for roads used by shuttles and buses are $R^{shuttle} = 0\ 78$ and $R^{bus} = 0\ 89$, respectively. These are averages over the arcs, weighted by distance. In the pessimistic scenario (Fig. 10b) these scaling factors go up significantly to $R^{shuttle} = 1\ 13$ and $R^{bus} = 1\ 17$. It is important to note that these networks are designed while taking congestion into account.



(a) Expected Scenario

(b) 50-50 Scenario

(c) Pessimistic Scenario

Fig. 7. ODMTS Designs without DBLs under Three Congestion Scenarios.

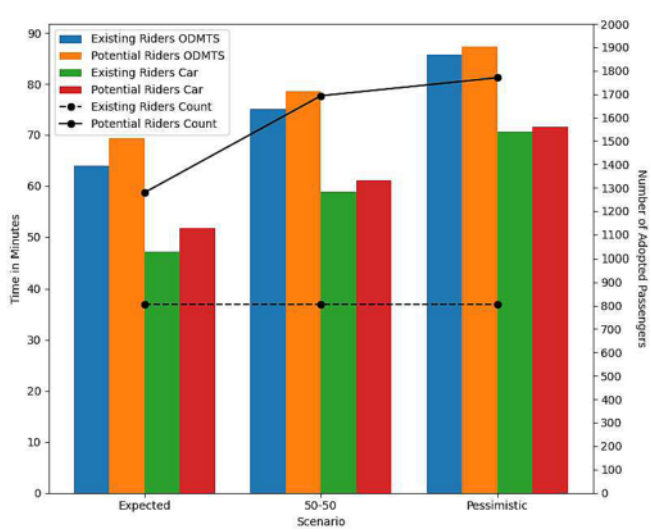


Fig. 8. Baseline Travel Times (left axis) and Counts (right axis) for Non-local Riders.

That is, the optimal designs avoid the extremely congested I-85 and distribute the remaining burden of traffic about equally over the shuttles and the buses. As congestion increases, substituting buses for shuttles makes this possible.

System Cost. Fig. 9 details the cost and revenue of the ODMTS under the different scenarios. Ridership increases with congestion, which leads to a small increase in revenue. The costs increase at the same time, mainly because of the increased travel time for buses and shuttles. Shuttle costs play the most prominent role, making up 79% to 85% of the total cost. The bus costs stay relatively constant because the ODMTS increases its reliance on shuttles as congestion increases. Fig. 9 also indicates that the ODMTS is profitable for the first two scenarios, but has a net cost of $0.42 per person in the pessimistic scenario. However, note that traditional transit systems are often heavily subsidized, where the ODMTS almost breaks even while serving more than 20k additional passengers and providing better access to transit. Furthermore, Auad et al. (2021) show that a stricter budget can be enforced by reducing the number of on-demand shuttles at the cost of a relatively small increase in waiting time.

6. Impact of Dedicated Bus Lanes

The previous section has shown that without DBLs, congestion has a

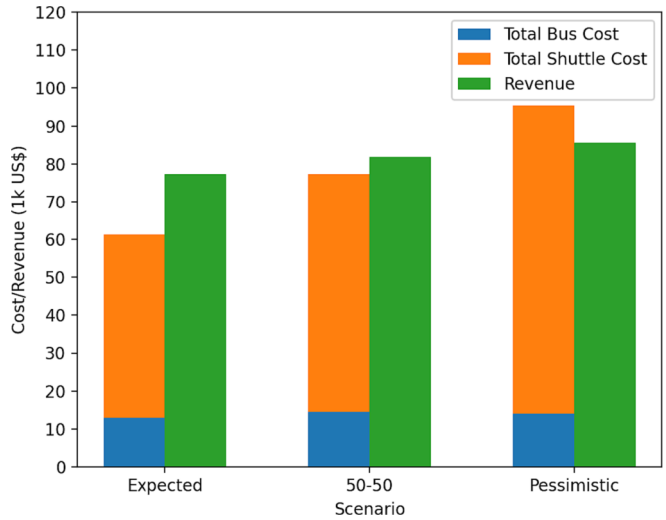


Fig. 9. Baseline ODMTS System Costs.

major impact on ODMTS travel times. This section studies to what extent DBLs can mitigate these negative effects, even when shuttles are still affected by traffic. The impact of DBLs is assessed by opening a DBL on I-85, reoptimizing the networks, and evaluating their performance. The ODMTS with DBLs is compared to the baseline in terms of design, travel times, passenger adoption, and cost of the system. Finally, this section explores how adoption changes with the adoption factor ρ.

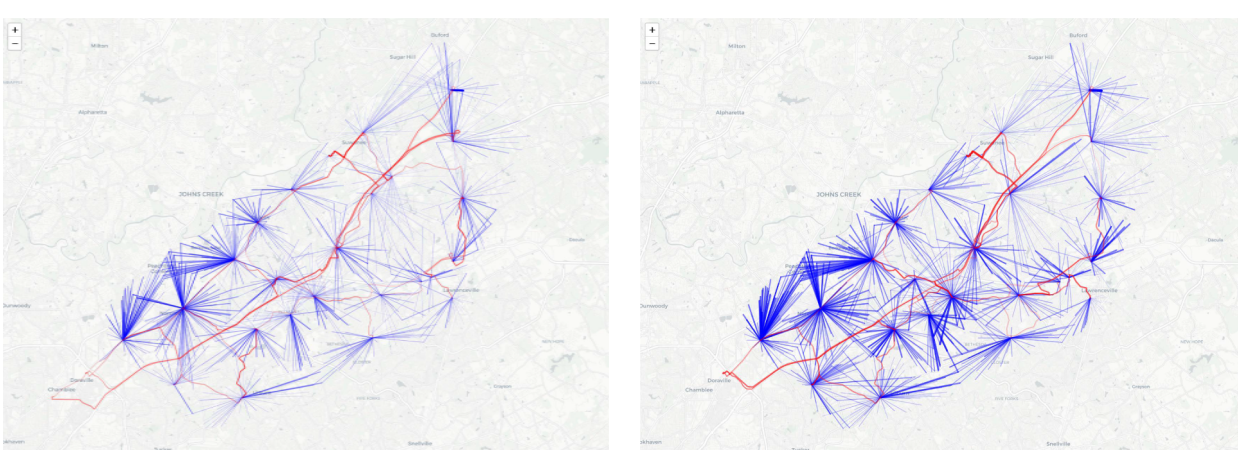
Network Redesigns with DBLs. Fig. 11 presents the ODMTS network redesigns that are optimized to leverage the DBLs (indicated by dashed lines). As a major change from the baseline ODMTS, the ODMTS with DBLs now include buses traveling south on I-85 from Gwinnett to Atlanta for all scenarios. This corridor was too congested to be used in the baseline, but the thick dashed lines in Fig. 11 indicate that riders now benefit extensively from these new bus connections. The local network within Gwinnett is similar across the scenarios, and also similar to the baseline. Recall that the baseline sees a substitution effect of buses for shuttles when congestion increases. This effect largely disappears as the important bus lanes are no longer affected by congestion (shuttle mileages are 65k, 66k, and 67k for the three scenarios, respectively). Overall the new networks suggest a major improvement for non-local travelers, and similar service for local travelers.

Travel Times and Adoption. Tables 3 and 4 support the view that DBLs bring significant benefits to non-local travelers while local service levels remain high. The tables separate adopted riders into those who would adopt even without DBLs (PreDBL) and those who would only switch to ODMTS if DBLs are implemented (PostDBL). Table 3 shows huge improvements for non-local travelers in terms of both travel time and adoption. Without DBLs, existing riders are expected to spend 64 min in the ODMTS, compared to 47 min by car. With DBLs, the average ODMTS travel time goes down to only 43 min and becomes faster than driving. This is possible because the buses are able to avoid traffic. PreDBL and PostDBL adopters also benefit from significantly improved travel times compared to ODMTS without DBLs. For example, PostDBL riders would have an average travel time of 107 min if they use ODMTS without DBLs, which reduces to only 60 min when DBLs are implemented. In fact, *DBLs are so effective that the travel times under the pessimistic scenario are better than the expected scenario without DBLs*. This is strong evidence that DBLs can mitigate the effects of congestion, even when shuttles are still affected by traffic.

The lower travel times for non-local riders result in a significantly increased adoption rate. For the expected scenario, the increase is 32 percentage point (from 52% to 84%), and for the pessimistic scenario it increases from 72% to 93%. This suggests that, in a congested environment, DBLs are able to attract almost all potential riders that can benefit from the traffic-free lane. Table 5 provides additional information on the mode distribution of the non-local adopters. Without DBLs, the only viable option is to take a shuttle to a bus station, take the bus to Chamblee or Doraville station and transfer to the rail. With DBLs, it becomes viable to directly take the bus to Atlanta rather than take a detour by rail, and this attracts a significant number of additional riders. Using the rail is still popular but, rather than transferring at Chamblee or Doraville station, riders get on the rail in Midtown Atlanta to complete the last mile.

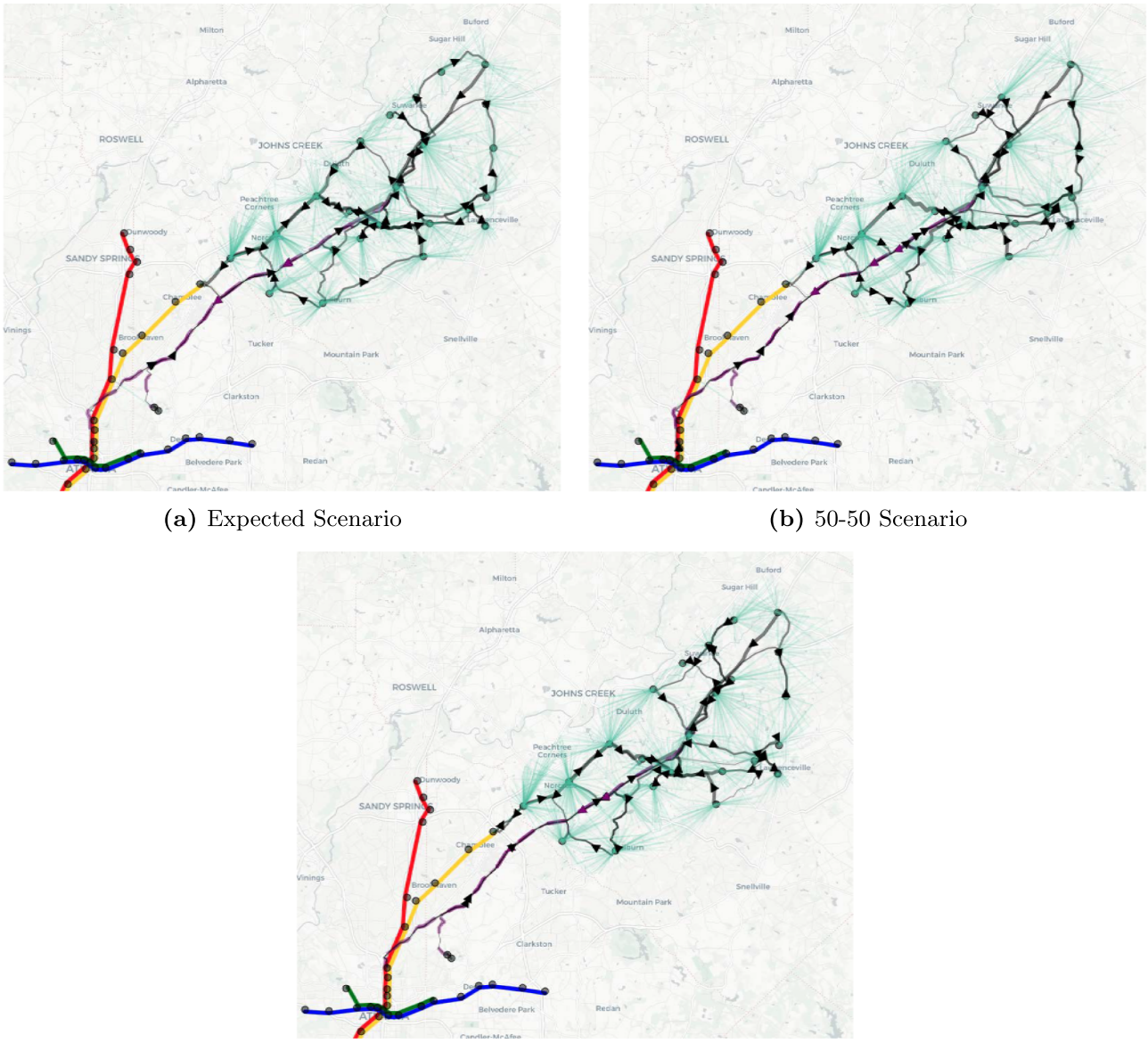
Non-local riders receive the most benefit from DBLs, but Table 4 shows that these improvements do not come at the expense of local transit users. Existing local riders see a small improvement in average travel time (up to 3 min in the pessimistic scenario), and the travel times for PreDBL adopters are more or less constant. Adoption of the ODMTS stays high, with over 60% of potential riders adopting in all cases. However, there is some decrease in adoption when DBLs are implemented in the 50–50 scenario (63% to 62%) and in the pessimistic scenario (66% to 63%). On the other hand, the DBL redesign also brings in new riders by significantly lowering their average travel time by up to 17 min in the pessimistic case. Overall the service level for the local travelers is comparable between the baseline and the DBL redesign, while the service level for non-local travelers improves significantly.

System Cost. Table 6 shows how DBLs impact the cost of the system. As congestion increases, DBLs become more useful compared to the baseline, and the table shows bigger investments in buses. For example,



(a) Expected Scenario (b) Pessimistic Scenario

Fig. 10. Baseline ODMTS Congestion Scaling Factors of Used Roads (darker is higher).



(a) Expected Scenario

(b) 50-50 Scenario

(c) Pessimistic Scenario

Fig. 11. ODMTS Designs with DBLs under Three Congestion Scenarios.

Table 3
Adoption and Travel Times for Non-local Riders.

		Ridership					Average Travel Time (minutes)			
		Existing	Adoption				Car	ODMTS		
Scenario	DBL	Count	Count	Rate	PreDBL	PostDBL	Existing	Existing	PreDBL	PostDBL
Expected	No	806	1,279	52%	-	-	47	64	70	70
	Yes	806	2,078	84%	1,263	815	47	43	54	47
50-50	No	806	1,693	68%	-	-	59	75	79	85
	Yes	806	2,153	87%	1,665	488	59	44	56	53
Pessimistic	No	806	1,770	72%	-	-	71	86	88	107
	Yes	806	2,307	93%	1,752	555	71	52	61	60

in the expected scenario, the redesign increases the shuttle cost by $3k while the bus cost remains the same. In the pessimistic scenario, on the other hand, investing $4k into buses allows the shuttle cost to be *reduced* by $7k, leading to a lower total cost. For the expected scenario and the 50–50 scenario, the increase in revenue balances out the increase in cost, resulting in only $0.03 difference in net profit per rider. For the pessimistic scenario, the lower system cost results in a savings of $0.10 per passenger. As a result, DBLs are effective in reducing travel times and increasing adoption without negatively affecting system cost. At the same time, DBLs do not resolve the issue that system cost increases with congestion, as depicted in Fig. 12. However, it is worth repeating that traditional transit systems tend to be heavily subsidized, where the

Table 4
Adoption and Travel Times for Local Riders.

		Ridership					Average Travel Time (minutes)			
		Existing	Adoption				Car	ODMTS		
Scenario	DBL	Count	Count	Rate	PreDBL	PostDBL	Existing	Existing	PreDBL	PostDBL
Expected	No	92	19,013	61%	-	-	10	20	11	31
	Yes	92	19,091	61%	17,942	1,149	10	18	11	19
50–50	No	92	19,706	63%	-	-	13	23	14	35
	Yes	92	19,266	62%	18,121	1,145	13	22	14	21
Pessimistic	No	92	20,646	66%	-	-	15	28	16	48
	Yes	92	19,618	63%	18,295	1,323	15	25	16	31

Table 5
Mode Distribution for Non-local Adopted Potential Riders.

	Expected		50–50		Pessimistic	
	No DBL	DBL	No DBL	DBL	No DBL	DBL
Bus	0	1	0	1	0	1
Bus and Rail	4	5	6	4	5	4
Shuttle and Bus	0	674	0	754	0	876
Shuttle, Bus, and Rail	1275	1398	1687	1394	1765	1426
Total	1279	2078	1693	2153	1770	2307

ODMTS almost breaks even when serving 20k additional passengers.

6.1. Sensitivity Analysis on Adoption Factor

This section analyzes how changing the adoption factor affects adoption by potential riders. Recall that the adoption factor ρ is used in the choice model to decide whether travelers adopt the ODMTS: Potential riders adopt the system if the ODMTS travel time is at most ρ times the travel time by car. Fig. 13 shows the different adoption rates for non-local potential riders when the network is designed for different scenarios and different adoption factors ranging from $\rho = 1\ 4$ (less willing to adopt) to $\rho = 1\ 6$ (more willing to adopt). Even without DBLs, adoption rates are typically high (above 50%) across scenarios and adoption factors. However, this is not the case for the expected scenario with adoption factor $\rho = 1\ 4$: Relatively low congestion favors driving by car. This, combined with less willingness to adopt the ODMTS, results in an adoption rate closer to 20%. Introducing DBLs in this situation has a major effect on adoption, which climbs to above 60%. This demonstrates the effectiveness of DBLs in attracting non-local riders.

Fig. 14 explains why DBLs are so effective in increasing adoption. It considers the networks designed for $\rho = 1\ 5$ and shows the ratio of ODMTS to car travel times for all non-local potential riders under the different scenarios. In other words, it shows the actual ratio that the potential riders observe, where riders adopt if the ratio is at most $\rho = 1\ 5$. These curves are very steep. For example, in the expected scenario without DBLs ridership quickly increases around the $1\ 5$ cut-off. Including DBLs makes the ODMTS more competitive and moves the curves to the left, resulting in a sharp increase in adoption, especially when adoption was previously low.

7. Conclusion

This paper studied the effect of congestion on ODMTS and to what extent Dedicated Bus Lanes (DBLs) can improve rider adoption. To enable this study, the paper introduced a method to create realistic congestion scenarios without querying all origin–destination pairs by combining data from multiple sources. Designing the ODMTS was modeled as a bilevel optimization problem in which potential riders choose whether to adopt the system based on the quality of the trip offered. These methods were then applied to perform a comprehensive case study in the Metro Atlanta Area, based on real data by Gwinnett County Transit and the Atlanta Regional Commission.

The case study revealed that, even with significant traffic, ODMTS is able to provide accessible transit, experiences high adoption, and almost breaks even in terms of cost. That being said, Interstate 85 from Gwinnett to Atlanta is so congested that the ODMTS avoids using this corridor at all. Instead passengers are transfered to take a detour through the rail system and experience long travel times. The congestion is not isolated to the highways, and slower shuttle trips are a major source of increasing costs as congestion increases.

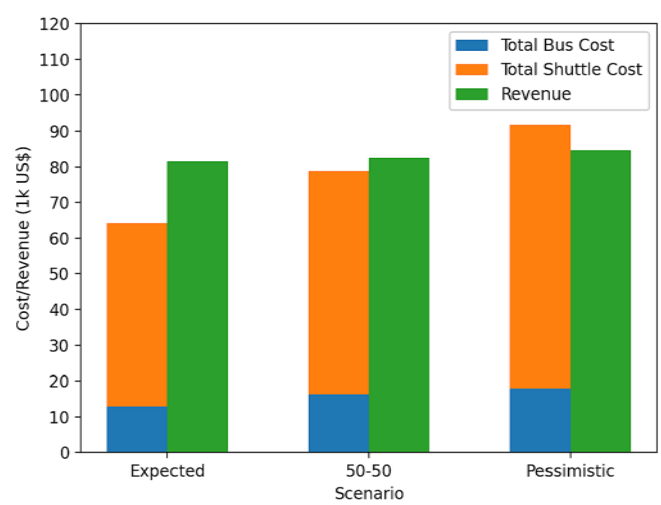
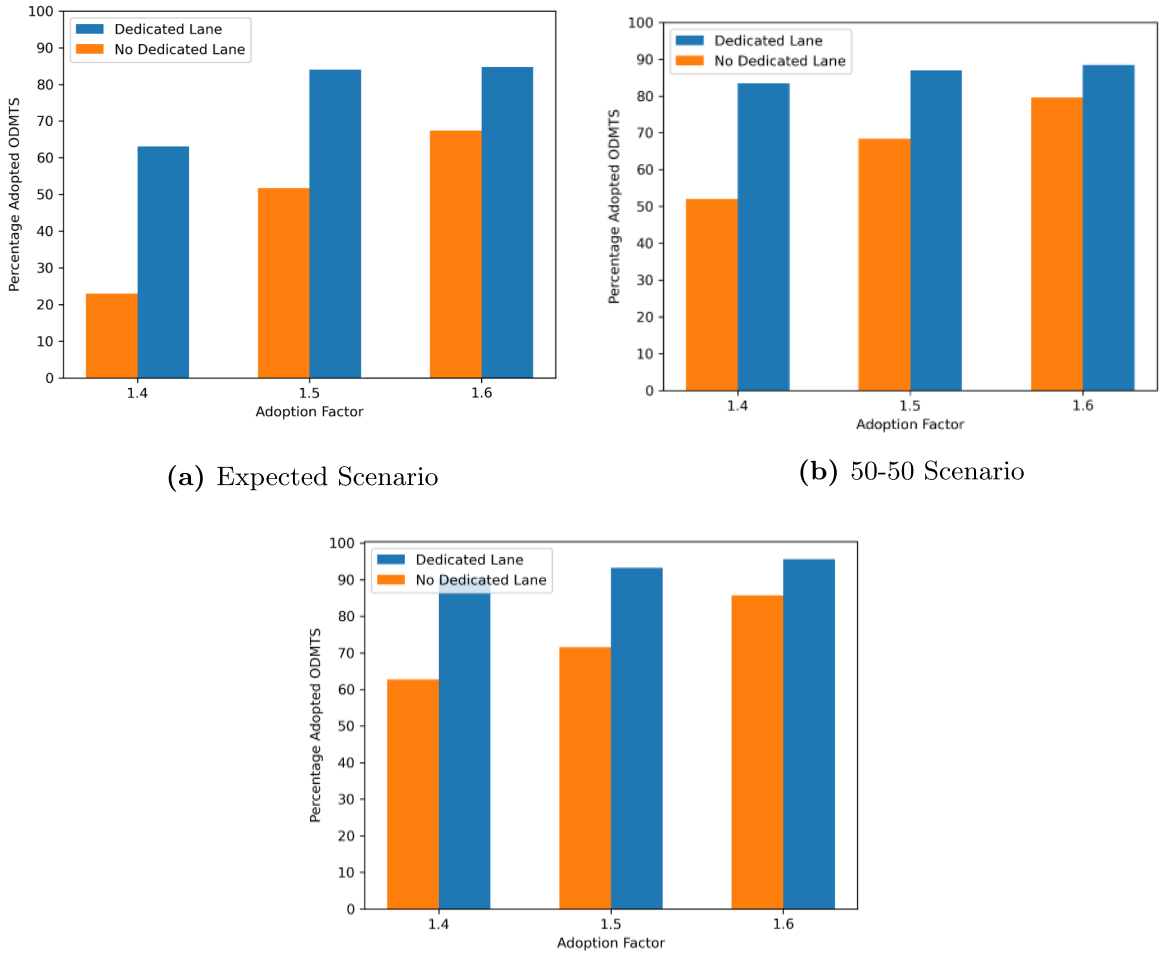


Fig. 12. ODMTS with DBLs System Costs.

Table 6
ODMTS System Costs.

			Cost				
Scenario	DBL	Ridership	Total	Bus	Shuttle	Revenue	Net Profit per Rider
Expected	No	20,292	$ 61k	$ 13k	$ 48k	$ 77k	$ 0.76
	Yes	21,169	$ 64k	$ 13k	$ 51k	$ 82k	$ 0.79
50–50	No	21,399	$ 77k	$ 14k	$ 63k	$ 82k	$ 0.20
	Yes	21,419	$ 79k	$ 16k	$ 63k	$ 83k	$ 0.17
Pessimistic	No	22,416	$ 95k	$ 14k	$ 81k	$ 85k	-$ 0.42
	Yes	21,925	$ 92k	$ 18k	$ 74k	$ 85k	-$ 0.32



(a) Expected Scenario

(b) 50-50 Scenario

(c) Pessimistic Scenario

Fig. 13. ODMTS Adoption Percentages for Non-local Potential Riders.

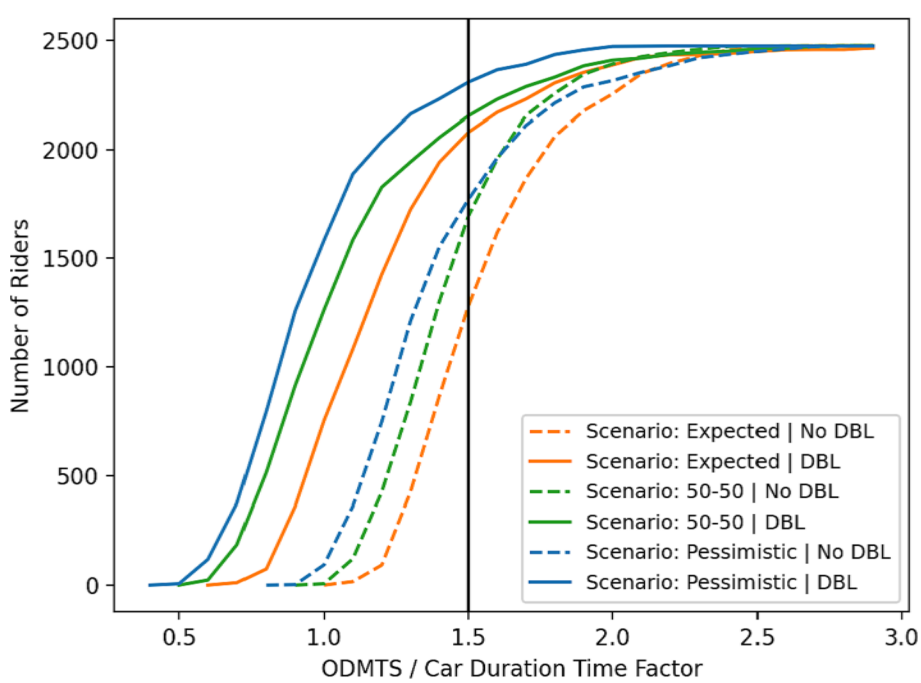


Fig. 14. Ratio of ODMTS to Car Travel Times for Non-Local Potential Riders.

The paper then studied the case where DBLs were added to the network and the ODMTS was reoptimized to benefit from the congestion-free lanes. The new networks feature buses on I-85 that are used extensively by riders. Non-local travel sees huge improvement in terms of travel time and ODMTS adoption. In fact, DBLs are so effective that the travel times under the pessimistic scenario are better than the expected scenario without DBLs. These improvements do not come at the expense of local travel, which sees a service similar to the baseline. While system costs still increase with congestion, DBLs do not contribute negatively to the operating cost.

This case study shows that DBLs may significantly increase ODMTS adoption. Future work should compare the benefit of DBLs in ODMTS across different cities, since Atlanta is a particularly congested city relying heavily on its highway system. Within various cities, studies may also involve scenarios with different bus transit frequencies and different sets of existing riders. Another direction for future research may be to improve the modeling of bus transit wait times to more accurately assess travel times.

CRediT authorship contribution statement

Jason Lu: Methodology, Software, Validation, Formal analysis, Investigation, Writing - original draft. **Anthony Trasatti:** Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft. **Hongzhao Guan:** Methodology, Software, Validation, Formal analysis, Investigation, Writing - original draft. **Kevin Dalmeijer:** Methodology, Software, Validation, Formal analysis, Investigation, Writing - original draft. **Pascal Van Hentenryck:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

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

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