



# Simulation based pre-implementation cost evaluation framework for integrated public transit services

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## ARTICLE INFO

### Keywords:

Fixed route transit  
On-demand transportation  
Demand response transit  
Transportation network company  
Agent based modeling  
Mobility-as-a-service (maas)  
Public transportation

## ABSTRACT

The growing demand for integrated and shared mobility services has resulted in a number of public–private partnerships, where public transit agencies and mobility companies collaborate to expand transit service coverage. Nonetheless, many collaborative efforts have failed due to financial restraints and low ridership. The failure of many of the integrated systems can be ascribed to the ineffective pre-implementation evaluation of the integrated system. The lack of a reliable performance evaluation tool capable of assessing the integrated system's performance prior to implementation could be the case of such failures. Considering this gap, this paper proposes a support tool for decision process of multimodal integrated transport system that examines the viability of an integrated mobility service system comprised of a Fixed Route Transit (FRT) service system and on-demand services. The decision process is powered by an agent-based simulation framework that tests scenarios covering various modal integration strategies. The on-demand services could be Demand Response Transit (DRT) and Transportation Network Company (TNC) services, that particularly act as feeders for FRT to ensure first and last-mile connectivity. This study proposes four integration-strategies with ten potential integration scenarios and four non-integration scenarios, comprising a total of fourteen possible scenarios to complete a trip between any origin–destination pair. Using the agent-based simulation model, various scenarios can be constructed for origin–destination pairs, and based on the generalized system cost, the preferred integration strategy can be selected. The proposed model analyzed the generalized system cost for each scenario by incorporating three key cost components: user cost, agency cost, and external costs. The proposed method was implemented on two different networks, which are the Sioux Falls network and a real-world case study of the Morristown city network in Tennessee, United States. Simulation outcomes indicate that 69% of trips in the Sioux Falls network and 73% of trips in Morristown could be connected to the existing FRT network using feeder services as first and last-mile connectivity solutions. The results suggest that a properly evaluated integrated system could enhance the accessibility of FRT significantly. Therefore, the proposed methodology assesses the advantages of the integrated system prior to its implementation, assisting transit planners and policymakers in the efficient execution of integration strategies and enhancing user experience and mobility.

## 1. Introduction

The rise of on-demand mobility services and the advancements in information and communication technologies have promoted the emergence of Mobility-as-a-Service (MaaS) systems. MaaS system enables the seamless integration of transportation services across numerous modes. These modes include the conventional Fixed Route Transit (FRT) and on-demand services like Demand Response Transit (DRT), or private taxi services from Transportation Network Companies (TNC), and other shared mobility options via a single platform (Pantelidis et al., 2020; Polydoropoulou et al., 2020; Vij et al., 2020; van den

Berg et al., 2022; Ho and Tirachini, 2024). Past studies indicate that integrated transport facilities enhance transit coverage, improve passenger experience, and promote a shift towards sustainable transportation (Aquad-Perez and Hentenryck, 2022; Stiglic et al., 2018; Itani et al., 2024). The increasing demand for integrated and shared mobility services has led to public–private partnerships between transit agencies and mobility companies to expand transit service coverage by ensuring the first and last-mile (FMLM) connectivity. However, such collaborative efforts often failed due to financial constraints and low ridership,

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<https://doi.org/10.1016/j.tranpol.2025.05.002>

Received 11 September 2024; Received in revised form 6 April 2025; Accepted 3 May 2025

Available online 26 May 2025

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which can be attributed to ineffective pre-implementation evaluations. It is noteworthy that there is a lack of reliable performance evaluation tool for integrated systems before deployment. To address this, there is a critical need for a comprehensive and cost-effective integration model. Such a model should not only benefit users but also assist transit planners and policymakers in adopting effective integration strategies to complement existing transit seamlessly.

Public transit, especially FRT, is crucial for providing affordable transportation and supporting sustainable economic growth. However, FRT's limited flexibility makes it effective primarily in densely populated areas, but less so in low-demand suburbs (Fittante and Lubin, 2016; Quadrifoglio and Li, 2009), where expanding coverage increases costs and travel times, often leading to fare hikes or reduced service (Mehran et al., 2020; Turcotte, 2008). In contrast, DRT are flexible on-demand transit services, with nearly 40% of U.S. transit agencies providing such services (Potts et al., 2010). While DRT can complement fixed routes and ensure economic flexibility and sustainability, it faces challenges like large fleet requirements, complex routing, and high costs (Basu et al., 2018; Giuffrida et al., 2020; Araldo et al., 2019; Sultana et al., 2018). While TNCs are privately owned on-demand, taking into account the flexibility of on-demand services, public transit authorities have partnered with micro-transit companies to enhance public transportation accessibility in many cities, as seen in cities like Boston, San Francisco, and Austin (Stiglic et al., 2018; Yan et al., 2019; Zhang and Khani, 2021; Ma et al., 2019; Lee et al., 2021; Blodgett et al., 2017; Feigon et al., 2018).

However, the success of such integration varies, with many pilot programs failing due to budget constraints and underestimated costs, as seen with Helsinki's Kutsuplus and the Chariot service (Westervelt et al., 2018; Estrada et al., 2020; Authority, 2016; Hawkins, 2019). High operating costs and affordability concerns often challenge these systems, as transit agencies strive to match the convenience of private TNCs while maintaining lower user cost (Zhu et al., 2021; Estrada et al., 2020). Therefore, quantifying system costs is vital to evaluating integrated transit systems. While operational cost models have been used to assess DRTs and TNCs, these evaluations should also consider social impacts (Goodwill et al., 2008; Turmo et al., 2018; Rahimi et al., 2018). The external costs of individual mobility, such as pollution and congestion, are often unaccounted for in trip fares, influencing mobility decisions (OECD, 2008; Mayeres et al., 1996; Van Essen et al., 2019). Recent studies suggest that greater awareness of mobility costs can promote sustainable behavior, highlighting the need for further research on the cost factors of integrated transportation systems (Kaddoura and Nagel, 2019; Axsen et al., 2020; Molloy et al., 2021; Schröder et al., 2022; Aravind et al., 2024a).

In the light of aforementioned challenges, this study develops an Agent-Based model (ABM) to simulate a multi-modal integrated system that aid to assess various integrated scenarios of FRT, DRT, and TNC within a single trip. Unlike prior research focusing on FRT and on-demand transit systems in isolation, our study focus on an examination of the synergies derived from their integrated operation. The study addresses the gap in literature assessing feasibility, economic viability, and social/environmental implications associated with integrating TNC and DRT services with FRT networks under a multi-modal Mobility as a Service (MaaS) framework. With this motivation, this study designs and fulfills the lack of a viable integration evaluation framework with the following three contributions: (i) model development for a multi-modal integrated system that allows users to evaluate the efficiency of the integrated FRT, DRT, and TNC systems to complete a trip, and determine the optimal leg sequence connecting the origin and destination; (ii) a decision support system that enables a realistic assessment of the costs and advantages of the emerging mobility paradigm for all stakeholders; (iii) performance evaluation of the model with respect to the different cost factors to assess the benefits of integration. The ABM simulation platform, allows for comprehensive testing of various integrated scenarios, offering granular insights for policy-related

decisions and facilitating straightforward extrapolation of multimodal integrated systems at different geographic scales. The proposed model benefits from both the analytical capabilities of public transit planning techniques and the agility of the agent-based simulation framework, making it generic and scalable.

The remainder of the paper is organized as follows, Section 2 presents a comprehensive literature review on MaaS studies and transit system integration, emphasizing research gaps. Section 3 describes the methodology for the agent-based simulation for the integration along with the various factors considered for building the simulation environment. Section 4 discusses results, with the first part covering an example network and the second part focusing on the simulation results of Morristown City, Tennessee. The final Section 5 summarizes the study by highlighting the key insights from the results, the significance of the findings, and the scope for improvement and future research scope.

## 2. Literature review

The concept of integrating FRT with various feeder services is not very new. Since the advent of paratransit, integration has been devised to offer several services, including the FMLM connection to the transit network (Liu et al., 2024). Studies have reported that the integration of on-demand transit as a feeder to the FRT system can promote the use of public transportation due to seamless FMLM connectivity (Shaheen and Chan, 2016; Shaheen and Cohen, 2020; Alonso-González et al., 2018). Recent studies explore public transit integration's viability, recommending utility maximization strategies for social, economic, and environmental benefits, promoting the shift from private vehicles to public transit (Mishra et al., 2012; Machado et al., 2018; Abduljabbar et al., 2021) which ultimately supporting greater transportation equity (Welch and Mishra, 2013; Chakraborty and Mishra, 2013; Sharma et al., 2020; Guo et al., 2024). Similarly, several studies have explored the potential of integrating FRT and on-demand transit, and some of the notable works include the research by Aldaihani et al. (2004), Wen et al. (2018), Stiglic et al. (2018), Narayan et al. (2020), Tang et al. (2023). Table 1 summarizes the past studies that explored the potential of integrating multiple feeder services into FRT systems.

Despite the substantial literature on public transit integration with feeder services, there still needs to be a better insight into the overall costs of various integration strategies and implementation challenges. Zhao et al. (2021) highlighted an absence of studies considering the integrated planning of fixed and on-demand transit services on realistic grounds. Nevertheless, there exist a few research efforts that offered perspectives on the cost of integrated mobility. For instance, Sangveraphunsiri et al. (2022) proposed a new model called Jitney-lite, a flexible form of collective transportation that helps to determine circumstances where one transport service has the lower generalized cost. Estrada et al. (2020) have optimized three on-demand transportation systems with different vehicle sizes deployed within a rectangular corridor to reduce user and agency costs. Their research demonstrated that implementing flexible integrated transit services could reduce the average cost per user. To balance service quality and operating costs, Li and Quadrifoglio (2009) created an analytical cost model to determine the number of zones served by a feeder line, but the study evaluated rectilinear vehicle movements between demand sites. Quadrifoglio and Li (2009) and Li and Quadrifoglio (2010) created analytical and simulation models to assess the service quality of the combined DRT-FRT network. These simulations determined the "critical demand density" for FRT-to-DRT transition. However, these studies primarily focused on evaluating the feasibility of local feeder service rather than optimizing the integrated FRT network design. Notably, there is a discernible gap in the literature concerning comprehensive cost models for integrated transit systems.

In the recent years, various studies have shown that, many new mobility services may exacerbate negative transportation externalities (Hensher, 2017; Clewlow and Mishra, 2017; Pangbourne et al.,

**Table 1**

A review of integrated public transit systems.

Author & Year	Study area	Data	Method	Objective	Key findings/Contribution
Calabro et al. (2023)	Paris, Singapore	Travel Demand Data	Continuous approximation	Proposes and evaluates Adaptive Transit, combining FRT and DRT depending on spatial and temporal demand density changes	Adaptive transport reduces the overall cost and improves user-related costs, especially in suburban areas and off-peak periods, compared to conventional transport methods
Matowicki et al. (2022)	European cities	Survey	Multinomial Logistic Regression (MLR) and Principal Component Analysis (PCA)	To understand the factors that contribute to the willingness to pay characteristics and attitudes of the prospective MaaS user	Indecisive users are older and earn less. Personal perspectives on shared economy, environmental friendliness, and social influence have a significant impact on MaaS competence. Notably, travel distance has no effect on MaaS use
Ma and Koutsopoulos (2022)	Chengdu, New York	TNC dataset	Advance Requests Ride Pooling (ARRP)	To reduce the impact of the uncertainty in future demand	Higher prior requests and readiness to cooperate can result in significant sustainability, service level, and fleet utilization gains. “near-on-demand” operations can benefit all participants (users, operators, cities)
van den Berg et al. (2022)	–	Hypothetical network	Analytical model, Numerical method	To examine the implications of the introduction of MaaS on prices, demand, and profits in the market for transportation services.	MaaS is operationalized in three ways: Integrator, Platform and Intermediary. The Integrator model appears to help society and customers. Instead of MaaS, the Platform approach tends to generate free competition. The Intermediary approach results in substantially higher prices.
Wang et al. (2022)	Detroit, Ypsilanti, Michigan	Survey	Latent class analysis	To examine how people's attitudes towards shared-use mobility services vary.	3 hidden segments: shared-mode enthusiast, shared-mode opponent, fixed-route loyalist. Transit is poorly accessible to shared-mode enthusiasts.
Grahn et al. (2021)	Pittsburgh	Ride request, Trajectory data	Heuristic methods	To develop a first and last-mile service operation model to match/route riders and vehicles.	Riders saved 18.6% when rides were coordinated with FRT. The case study shows possible reductions in journey time and user reliability of 51% and 53.8%, respectively. Prioritizing trips can improve travel time reliability without increasing user fees.
Han et al. (2021)	Leeds Metropolitan Area	Transit data	Evolutionary optimization, Population-based incremental learning algorithm	To evaluate a potential CAV route's quality by quantifying geographic accessibility improvements on an abstract multi-modal transport network.	The general ability of solvers to identify key PT stops that must be serviced by an optimal route is evidenced in the study by the frequency of stop selection
Leffler et al. (2021)	Hypothetical, Stockholm	Hypothetical	Simulation model	To develop a simulation model and evaluate fixed versus on-demand operational designs of an automated feeder service	It is proven that combining DRT on branches with fixed services on the trunk reduces overall median waiting times for all DRT scenarios.
Zhao et al. (2021)		Hypothetical	Two step heuristic algorithm, Genetic algorithm	To jointly optimize regular and DRT services while reducing passenger travel time and fleet numbers	DRT replaces regular transit in low-demand areas, improving overall network performance. Proposed model identified sub-optimal solution in a reasonable time

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2018; Zhu et al., 2020; Suatmadi et al., 2019; Tirachini, 2019). Prior studies, such as van Vliet et al. (2011), Clerck et al. (2018) and Yazdanie et al. (2016), evaluated the energy efficiency, cost, and greenhouse gas emissions of various transport modes and emphasized the importance of adequately considering them for a sustainable transportation system. Furthermore, research by Gössling et al. (2022) revealed that the total costs of private car ownership for both the user and society are significantly high compared to a public mode of transportation. Motivated by previous research on the environmental and social cost of different transportation modes and the absence of literature counting integrated network externalities, this study evaluates an integrated system using user, agency, and social costs.

Among the various optimization/simulation models developed to evaluate the efficiency and viability of integrated public transit systems, the Agent-Based Simulation models have received growing popularity

in recent years (Wen et al., 2018). Notably, ABM is beneficial for comprehending the complexity of transport systems and the emergent phenomena resulting from the interaction of multiple agents with various objectives and behaviors (Pira et al., 2017; Marcucci et al., 2017). Giuffrida et al. (2020) utilized ABM to compare a DRT service in Dubai with smaller ridesharing vehicles, revealing that route choice strategy is critical in balancing operator and user costs. Wen et al. (2018) devised an ABM simulation to evaluate the viability and efficacy of the integrated demand-supply interaction framework, in which autonomous vehicles served as a feeder system for the FRT. The integration model proposed in their study demonstrated that it could increase transit system efficacy, decrease travel time, and reduce vehicle requirements, especially in low-density suburban regions. Scheltes and Correia (2017) and Shen et al. (2018) utilized an ABM model to analyze the performance of the automated last-mile transportation system.

Table 1 (continued).

Author & Year	Study area	Data	Method	Objective	Key findings/Contribution
Feneri et al. (2020)	Rotterdam, Amsterdam, and Utrecht	Survey	Error Components Logit (ECLoGit) model	To examine the impact of a set of variables on MaaS transportation usage	Mode adoption is determined by monthly costs and discounts for various modes. Contrary to predictions, travelers who now drive or ride in privately owned cars are less likely to continue using their current mode than walkers or bikers
Huang et al. (2020)	Nanjing, China	Empirical data, CB company	Mixed-integer program, 2-phase optimization	To maximize the operators revenue	The static phase can reduce the number of routes needed to fulfill all verified requests. Re-optimizing the service network can save operational costs by 22.8%. A lower average transit fare indicates more requests
Narayan et al. (2020)	Amsterdam	Hypothetical	Agent based simulation framework	To develop an integrated multimodal route choice and assignment model that minimizes travel impedance	When modes of operation are combined, flexible PT covers 30% of the trip. Beyond 5% of travel demand, the sensitivity study of Flexible PT fleet size indicates no substantial gains in service.
Levin et al. (2019)	Sioux Falls network	Hypothetical	Linear program, Rolling horizon method	To optimally integrate SAVs with transit reducing overall travel time.	A small SAV fleet means taking transit saves time. Transit minimizes wait time but increases travel time. The technology may assist future SAV operators and planners predict transportation congestion.
Shen et al. (2018)	Singapore	CEPAS data	Agent based supply side simulation	To Propose and simulate an integrated autonomous vehicle and public transportation system	The integrated system can improve service quality, reduce road usage, be financially viable, and utilize bus services more efficiently.
Wen et al. (2018)	Major European city	Transit data	Agent based simulation platform, Discrete choice model	To design, simulate, and evaluate systems that combine autonomous vehicles and public transportation	Service vs. cost tradeoffs with implications for fleet sizing. Allowing advance requests and combining fare and ride-sharing helps service integration
Aldaihani et al. (2004)	–	Hypothetical	Analytical model	To determine the optimal number of zones in a region where on-demand serve each zone	Trades off the passenger cost, on-demand vehicles, and fixed bus lines to determine the optimal number of zones
Aldaihani and Dessouky (2003)	Antelope Valley in California	Transit data	Heuristic Algorithm, Tabu Search	To create a hybrid routing problem by combining fixed route with general pickup and delivery	Using a hybrid service route (for 18.6% of requests) reduces on-demand vehicle distance by 16.6% and overall trip time by 8.7%.

While, Basu et al. (2018) and Oh et al. (2020) used an ABM model to demonstrate the effects of automated mobility-on-demand services on urban transportation. These studies collectively emphasize ABM's potential in assessing the viability of various integration scenarios, owing to its ability to capture the dynamic interactions among diverse agents within the transit ecosystem.

Notwithstanding all research efforts on public transit integration, the literature review reveals a need for a preliminary evaluation of the economic viability of public transit integration with feeder services for effective field deployment. Notably, the existing body of literature lacks comprehensive cost estimations encompassing user, agency, and external perspectives. Furthermore, to the best of our knowledge, no research has examined the social and environmental benefits of the integrated public transit system.

### 3. Methodology

This study develops a simulation platform to perform the viability assessment of various integrated public transportation scenarios. The goal is to improve transit accessibility through FMLM connectivity, and minimize costs for agencies, users, and due to socio-economic externalities. The model can test the impact of various modifications in each integrated scenario and this simulation platform offers a comprehensive testing ground for policy-related measures, operating at a granular level, which can be easily extrapolated to different scales. The system is designed to be easily understandable from both user and agency perspectives. The following sections provide more insight into each component of the integration strategy and evaluation.

#### 3.1. Integrated transit scenarios

Integrated transit scenarios refer to the trip an agent makes from an origin to destination using multiple modes. It may thus consist of FRT services, DRT services, and services by TNCs, either individually or in combination. The study proposed four integration-strategies with ten different possible scenarios, and four non-integration scenarios, summing to total 14 scenarios with which a trip can be completed. The characteristics of each integration-strategy and scenario are outlined in Table 2.

The four integration-strategies involve connecting on-demand services as feeders to FRT service, either individually ( $INT_{FRT,DRT}$ ,  $INT_{FRT,TNC}$ ) or in combining both on-demand services in one ( $INT_{FRT,DRT,TNC}$ ). The fourth integration-strategy, though it is not quite often preferred, it completes a trip using only on-demand services in two legs with DRT and TNC in combination ( $INT_{DRT,TNC}$ ). Within each integration-strategy, the number of trip legs and the modal sequence are permuted to determine the different scenarios within them. Non-integration scenarios are single-leg trips using a specific mode: that is either DRT, TNC, FRT or an hypothetical FRT and denoted respectively as  $S_{DRT}$ ,  $S_{TNC}$ ,  $S_{FRT}$ ,  $S_{FRT^{hyp}}$ . The hypothetical scenario assumes the existence of hypothetical FRT stops within a walkable distance of both origin and destination, as well as the availability of FRT schedules. All these plausible scenarios for an O-D pair were generated using the Agent-Based Model



**Table 2**  
Integration-strategies and scenarios.

Integration-strategy	Scenario	Leg-1	Leg-2	Leg-3	Properties
Non-integrated scenarios	$S_{DRT}$	DRT	×	×	Possible for every O-D pair
	$S_{TNC}$	TNC	×	×	Possible for every O-D pair
	$S_{FRT}$	FRT	×	×	Constrained to be possible if there is an FRT stop within the walking radius of origin and destination
	$S_{FRT^{Hyp}}$	FRT	×	×	Hypothetical Scenario assuming an FRT stop within the walking radius of origin and destination, possible for every O-D pair
FRT, DRT integration ( $INT_{FRT,DRT}$ )	$S_{DRT-FRT}$	DRT	FRT	×	Constrained to be possible if there is an FRT stop within the walking radius of destination Two leg scenario with DRT as the first-mile connectivity
	$S_{FRT-DRT}$	FRT	DRT	×	Constrained to be possible if there is an FRT stop within the walking radius of origin Two leg scenario with DRT as the last-mile connectivity
	$S_{DRT-FRT-DRT}$	DRT	FRT	DRT	Constrained to be possible if the ratio of FRT length in the trip to total trip length ( $\zeta_{trip}$ ) is larger than FRT coverage of network ( $\zeta_{network}$ ) If there is no FRT stop within the walking radius of both origin and destination, DRT provides the FMLM connectivity
FRT, TNC integration ( $INT_{FRT,TNC}$ )	$S_{TNC-FRT}$	TNC	FRT	×	Constrained to be possible if there is an FRT stop within the walking radius of destination Two leg scenario with TNC as the first-mile connectivity
	$S_{FRT-TNC}$	FRT	TNC	×	Constrained to be possible if there is an FRT stop within the walking radius of origin Two leg scenario with TNC as the last-mile connectivity
	$S_{TNC-FRT-TNC}$	TNC	FRT	TNC	Constrained to be possible if the ratio of FRT length in the trip to total trip length ( $\zeta_{trip}$ ) is larger than FRT coverage of network ( $\zeta_{network}$ ) If there is no FRT stop within the walking radius of both origin and destination, TNC provides the FMLM connectivity
DRT, TNC, FRT integration ( $INT_{DRT,TNC}$ )	$S_{DRT-FRT-TNC}$	DRT	FRT	TNC	Constrained to be possible if the ratio of FRT length in the trip to total trip length ( $\zeta_{trip}$ ) is larger than FRT coverage of network ( $\zeta_{network}$ ) FMLM connectivity to FRT provided by DRT and TNC respectively
	$S_{TNC-FRT-DRT}$	TNC	FRT	DRT	Constrained to be possible if the ratio of FRT length in the trip to total trip length ( $\zeta_{trip}$ ) is larger than FRT coverage of network ( $\zeta_{network}$ ) FMLM connectivity to FRT provided by TNC and DRT respectively
DRT, TNC integration ( $INT_{DRT,TNC}$ )	$S_{DRT-TNC}$	DRT	TNC	×	Possible for every O-D pair
	$S_{TNC-DRT}$	TNC	DRT	×	Possible for every O-D pair

### 3.2. Agent-based simulation framework

ABM is a computational model for simulating the activities and interactions of autonomous agents to comprehend the behavior of the system and what determines its outcomes (Talebian and Mishra, 2018; Mishra et al., 2022). Unlike traditional simulations, ABM relies on limited agent behavioral rules, allowing emergent patterns to unfold (Inturri et al., 2019). ABM can provide an appropriate environment for testing transport systems to determine the possible efficacy and application of transport services under different configurations. Fig. 1 illustrates the basic structure of the proposed ABM simulation framework. It consists of three essential components: the agent, the transport modes, and the transport networks, which together contribute to the estimation of the generalized system cost. The trip makers are modeled as agents and they are assigned with specific personal attributes in order to capture the realistic behaviors of heterogeneous population. The agent draws requests from the OD matrix and is characterized by various factors, and intent to complete their trip between a pair of origin ( $o$ ) and destination ( $d$ ), with minimal generalized system cost ( $f(c)^{od}$ ) for every scenario ( $j$ ). The personal attributes of agents considered in this study are:

- Walking speed ( $v_{walk}$ )
- Time of trip request ( $t_r$ )
- Out-vehicle travel time ( $t_j^{ov}$ ),  $t_j^{ov} = \sum_n^N t_{j,m}^{wt}$   
where

$$\begin{aligned}
 m &= \text{Chosen transit mode in scenario } j \\
 N &= \text{Maximum number of transfer or legs in scenario } j \\
 t_{j,m}^{wt} &= \text{Waiting time for mode } m \text{ in scenario } j
 \end{aligned}$$

Furthermore, in this study each agent can choose among three modes, namely FRT, DRT, and TNC. However the simulation model

is flexible to incorporate/remove any particular mode, for a comprehensive use of the proposed model framework. The different modes in the study are defined by their characteristic speed, fare, operating and running costs, and surge factors. The simulation environment is the transportation network that consists of two topological graphs: the local routable road network ( $\mathcal{G}^{net}$ ) and a designated FRT route network ( $\mathcal{G}^{FRT}$ ). Fig. 2 shows the topological graph of the local route network and FRT network. The supply, demand, and the environment of the integrated system for the ABM are detailed in the following sections.

#### 3.2.1. Supply

**Routable Network:** The network data comprises of the local road network and the FRT network, represented by a set of nodes and the connecting links. The DRT and TNC modes considered in the study utilizes the local road network and the FRTs use only the dedicated FRT routes with predefined stops, which is a subset of the local network. The local network was defined as a graph  $\mathcal{G}^{net}(\mathcal{V}, \mathcal{A})$ , where  $\mathcal{V} = [v_0, v_1, \dots, v_n]$  is the set of vertices or nodes in the network and  $\mathcal{A} = [(v_i, v_j) : v_i, v_j \in \mathcal{V}, i \neq j]$  is the set of links connecting these nodes. The FRT network is also defined as a graph  $\mathcal{G}^{FRT}(\mathcal{V}^{FRT}, \mathcal{A}^{FRT})$ , which is formed with a subset of vertex set  $\mathcal{V}$ , and the FRT stops are defined as  $\mathcal{V}^{FRT} = \{[v_1^{FRT}, v_2^{FRT}, \dots, v_p^{FRT}] | \mathcal{V}^{FRT} \subset \mathcal{V}, i = 1, 2, \dots, p\}$ , where  $p$  is the total number of FRT stops. Similarly,  $\mathcal{A}^{FRT}$  indicates the links that are designated FRT routes  $\mathcal{A}^{FRT} = [(v_i^{FRT}, v_j^{FRT}) : v_i^{FRT}, v_j^{FRT} \in \mathcal{V}^{FRT}]$ , also  $\mathcal{A}^{FRT} \subset \mathcal{A}$ . It was assumed that, at the nodes where the links intersect, various interactions between transportation modes and agents will take place that include:

- A node can serve as either the origin or destination for an agent, where they can be picked up or dropped off by vehicles.
- A node can act as a transfer point, where the transfer between transport modes takes place

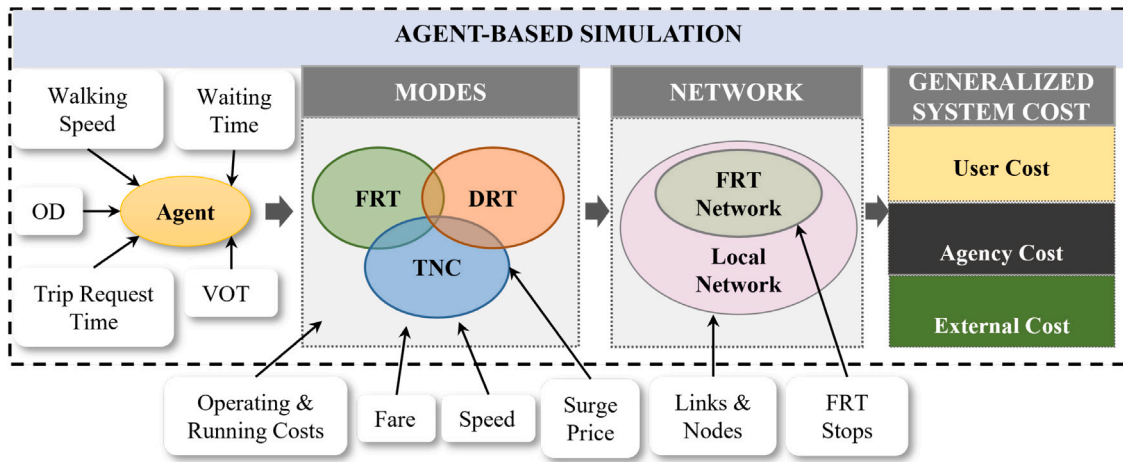


Fig. 1. Overview of simulation framework.

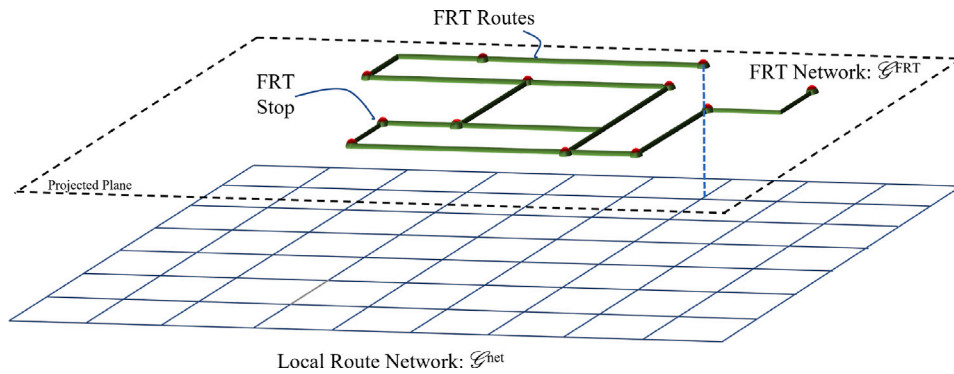


Fig. 2. Topological graph of local route network and FRT network.

- iii. A node in an FRT network can act as the designated stops of FRT.

**Modal Fleet and Modal Costs:** The three different travel modes considered in this study are conventional FRTs, and on-demand services provided by DRTs and TNCs. DRTs and TNCs are modeled as flexible, door-to-door services, resembling traditional taxi services and are not shared, while FRTs follow fixed routes and schedules. The model assumes a homogeneous fleet within each category, with all vehicles in a particular category will have the same characteristics such as capacity, speed, and route choices. Nevertheless, the simulation platform has the flexibility to add other modes with varying characteristics. The cost for the public agencies to operate and run ( $\gamma_{i,m}^{operational}$ ) the three modes considered in the study was collected from previous literature and transit agencies in the United States (Dickens and Kahana, 2022).

The study also assumes that public transit agencies directly operate FRT and DRT, but not TNC. This assumption is based on the premise that DRT services are primarily operated by the public transit agencies to complement the FRT services and provide a flexible mobility option to the transportation-disadvantaged population. Meanwhile, any privately operated on-demand or demand-responsive services are categorized under TNCs in this study. While DRT and FRT operating expenses are available, TNC costs, being dynamic and private-operated, are not directly accessible. In the absence of a public-private partnership, TNC operating costs are typically covered solely by TNC operators. However, to promote integration, public agencies might incentivize private TNC partnerships by subsidizing a percentage of TNC operating costs. To evaluate such incentives, this study incorporates in the simulation framework that public agencies can bear a certain percentage of the operating and running costs of TNCs and that is equivalent to the

operating and running costs of FRT. With this flexibility, it is possible to strategize the incentive plan for public-private integrated system.

**Modal Fares:** The study determines the fares for the various modes of transportation by studying the fares established by public agencies and by observing fare patterns in the United States.

- i. **TNC Fares:** The TNC fare was determined by analyzing data collected from Uber and Lyft in the study area across multiple days and times for all unique origin-destination pairs. The observed data was used to calculate trends in TNC fare and waiting time. Fig. 3 illustrates the variation in TNC fares with respect to distance traveled. The TNC fare was found to be constant (denoted as base-fare:  $\gamma^{base}$ ) up to certain distance known as critical distance ( $d_{crit}$ ) and thereafter the fare is linearly increasing with distance traveled. During peak hours, TNC fares experience surge pricing, where the fare for trips is adjusted by multiplying the base fare with a surge multiplier to recreate the peak hour demand price. Surge multipliers are discrete; they range from a minimum value ( $\mathcal{C}_{lower}^{Surge}$ ) of 1.2 to a maximum value ( $\mathcal{C}_{upper}^{Surge}$ ) that is different for each city (Chen, 2016). In this study, during the peak hour, the surge factor is randomly selected from [ $\mathcal{C}_{lower}^{Surge} = 1.2, \mathcal{C}_{upper}^{Surge} = 1.5$ ]. This pricing model followed by the TNCs, can partially capture real-world supply fluctuations by indirectly addressing supply-demand imbalances through surge pricing, where higher fares typically correspond to reduced availability.
- ii. **DRT Fares:** The DRT fare is assumed to be a penalized version of the TNC fare, except when it is served as a feeder to the FRT system. When DRT serves as a feeder to FRT, the system uses a flat fare regardless of the distance traveled, ensuring affordability and encouraging multimodal connectivity. However, when

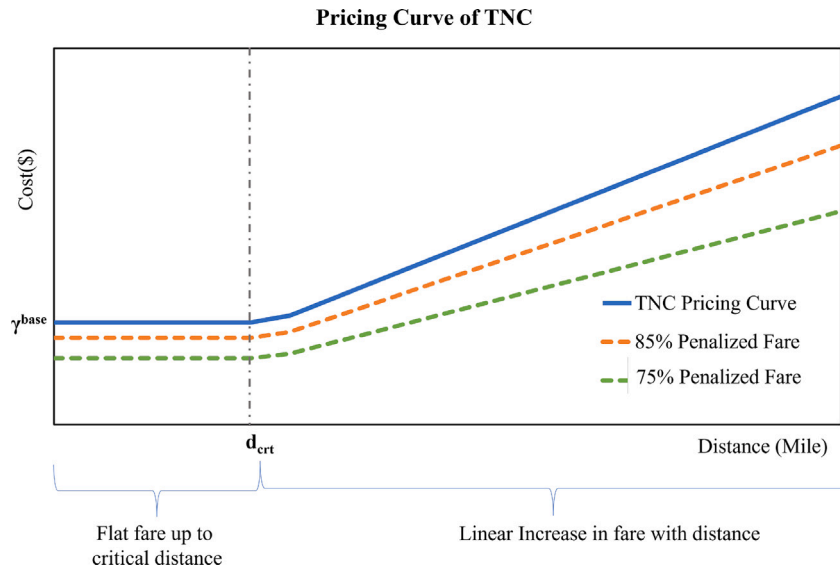


Fig. 3. Relation between the TNC fare and distance traveled.

DRT alone is used to complete a trip from origin to destination, it behaves similarly to TNC and it is not feasible to operate on the flat fare system. Therefore, this study assumes TNC-like but penalized fare for DRT, reflecting operational constraints and the need for cost recovery.

- iii. FRT Fares: FRT fare structures vary across different regions, with both flat fare and distance-based fare systems commonly used in the U.S. Typically, distance-based fares are more prevalent in high-density urban areas, whereas flat fares are commonly adopted in rural and suburban transit systems to ensure affordability and accessibility (Taylor and Morris, 2015; Liu et al., 2017; Nishiuchi et al., 2024). In this study, the FRT system serves all its tickets with a flat fare irrespective of the distance. The primary objective of traditional public transit services that are operated by public agencies is to ensure the public's accessibility to various activities, and therefore, surge factors do not play a role in the FRT fares.

**Modal Waiting Time:** Intuition combined with prior experience suggests that the distribution of waiting time is likely to be positively skewed (Pratt et al., 2000; Roy and Basu, 2021), with frequency (or probability) decreasing asymptotically as the value of waiting time grows. In light of these facts, to model the associated randomness of modal waiting times, this study considered three continuous probability distributions—Gamma, Log-normal, and Weibull for all the modes.

### 3.2.2. Demand

The demand is represented by agents travel needs, who start with predetermined travel plan at a defined trip time. These agents evaluate the attractiveness of different scenarios based on the cost of the trip and adjust their travel patterns to maximize utility. An income-based segmentation of the study area was proposed to generate random demand and it was assumed that the VOT for trips originating from these zones reflects the income level of the population of the zones (Kockelman et al., 2013; Fournier and Christofa, 2020; Sabyasachee Mishra et al., 2022; of Travel Time, 1977). The agent selects trip legs and modes based on their utility, considering the generalized system cost—a combination of monetary and non-monetary trip costs. For every choice made by the agent, the corresponding cost incurred for making the trip were calculated. These estimates essentially give insight into the viability of the integration of multiple modes and their potential benefits in terms of relative attractiveness. It is to be noted that, the demand for DRT and TNC were assumed to be elastic and solely reliant on their respective generalized system cost.

### 3.2.3. Generalized system cost

The utility of the integration of DRT and TNC with FRT network was estimated using the generalized system cost. The generalized system cost has three components, which are the user cost ( $f(c)_{user,j}^{od}$ ), agency cost ( $f(c)_{agency,j}^{od}$ ), and external cost ( $f(c)_{ext,j}^{od}$ ). For every scenario ( $j$ ), and for each origin destination pair  $o-d$ , the generalized system cost are computed as a summation of the user, the agency, and the external cost.

**User Cost :** The user cost ( $f(c)_{user,j}^{od}$ ) is the perceived utility of a mode or mode combinations by the users. It is calculated in terms of different time and monetary cost components, which include considering the fare, in-vehicle travel time ( $t_{j,m}^{iv}$ ), and out-vehicle travel time ( $t_{j,m}^{ov}$ ). The time components are translated into monetary value using VOT, which is based on the income category of the tripmaker. Eq. (1) given Box I describes the user cost for every scenario  $j$ , ( $j \in [1, 14]$ ), from each origin destination pair ( $o, d$ ), and for each user.

$$t_{j,m}^{iv} = d_{j,m} / v_{j,m} \quad \forall j \in [1, 14] \quad (2)$$

$$v_{j,m} = f(k^j) \quad \forall j \in [1, 14] \quad (3)$$

Here, the traffic speed is assumed to be the function of traffic density. Also, the traffic state was assumed to follow a triangular flow-density relationship (Ref. Fig. 4).

$$t_{j,m}^{ov} = \delta 3_{j,m} \times t_{j,m}^{wt} \quad \forall j \in [1, 14] \quad (4)$$

$M$	= Number of available transit modes, { FRT, DRT, TNC }
$\lambda_{od}$	= Value of travel time for the trip from origin $o$ to destination $d$
$t_{j,m}^{iv}$	= In-vehicle travel time for mode $m$ in scenario $j$
$t_{j,m}^{ov}$	= Out-vehicle travel time for mode $m$ in scenario $j$
$t_{r,od}$	= Time at which the trip is requested from origin $o$ to destination $d$
$t_{j,m}^{wt}$	= Waiting time for mode $m$ in scenario $j$
$rand(a, b)$	= A function to generate a random number between $a$ and $b$

$$f(c)_{user,j}^{od} = \begin{cases} \sum_m^M [\lambda_{od} \times (t_{j,m}^{iv} + t_{j,m}^{ov})] + \\ [ \gamma_{j,m}^{base} \times \delta 1_{j,m} + \gamma_{j,m}^{dist} \times (d_{j,m} - d_{crt,m}) \times \delta 2_{j,m} ] * rand([\mathcal{C}_{lower}^{Surge}, \mathcal{C}_{upper}^{Surge}]) & \text{if } t_{r,od} \in [6.am, 8.am][3.pm, 5.pm] \\ & \& m = TNC \\ \sum_m^M [\lambda_{od} \times (t_{j,m}^{iv} + t_{j,m}^{ov})] + \\ [ \gamma_{j,m}^{base} \times \delta 1_{j,m} + \gamma_{j,m}^{dist} \times (d_{j,m} - d_{crt,m}) \times \delta 2_{j,m} ] & \text{otherwise} \end{cases} \quad (1)$$

Box I.

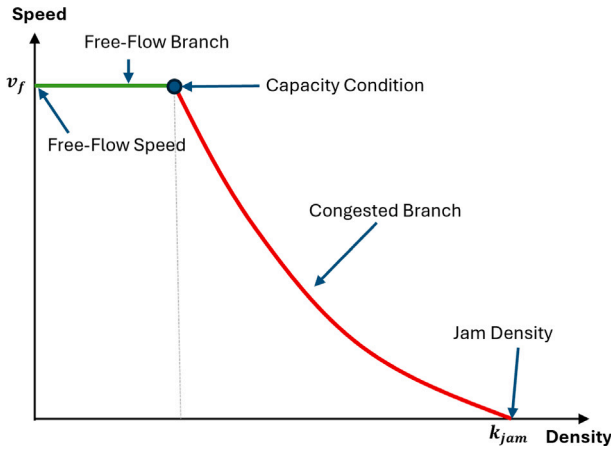


Fig. 4. Relation between speed and density assumed in the study.

- $\gamma_{j,m}^{base}$  = Base Fare for mode  $m$  in scenario  $j$
- $\gamma_{j,m}^{dist}$  = Fare per unit distance for mode  $m$  in scenario  $j$
- $v_{j,m}$  = Average travel speed for mode  $m$  in scenario  $j$
- $k^j$  = Traffic density  $k$  in scenario  $j$
- $v_f$  = Free flow travel speed
- $k_{jam}$  = Jam density
- $d_{crt,m}$  = Critical distance for mode  $m$
- $d_{j,m}$  = Trip distance for mode  $m$  in scenario  $j$
- $\mathcal{C}_{lower}^{Surge}$  = Lower limit of surge multiplier
- $\mathcal{C}_{upper}^{Surge}$  = Upper limit of surge multiplier
- $\delta 1_{j,m}$  = 1 If base fare is present, else 0
- $\delta 2_{j,m}$  = 1 If distance based fare is present for mode  $m$  in scenario  $j$ , else 0
- $\delta 3_{j,m}$  = 1 if respective waiting time is applicable for mode  $m$  in scenario  $j$ , else 0

In the cost evaluation framework, VOT is already incorporated, assigning a monetary value to all wait times, including travel time within a multimodal trip. Consequently, an additional transfer cost is not included in the model. Since the waiting time penalty inherently accounts for the inconvenience of transfers, introducing a separate transfer cost may risk overestimating the overall travel burden.

**Agency Cost:** Agency cost ( $f(c)_{agency,j}^{od}$ ) is the cost perceived by the agencies in providing the service to the users through any of the defined scenarios. When agencies report cost per passenger mile, the calculation typically distributes total expenses over total passenger miles traveled, simplifying the cost structure (Ride the Rapid, 2024). This cost considers the operating and running costs, which include the cost of fleet, distance or time-based costs, the labor cost including driver, maintenance staff, and the per day procurement cost of the fleets used. Eq. (5) describes the agency costs for every scenario  $j$  for each

origin destination pair ( $o, d$ ).

$$f(c)_{agency,j}^{od} = \sum_m^M [\gamma_{j,m}^{operational} \times d_{j,m}] \quad \forall j \in [1, 14] \quad (5)$$

where,

$\gamma_{j,m}^{operational}$  = Operating and running cost per unit distance for transit mode  $m$  in scenario  $j$

**External Cost:** External cost ( $f(c)_{ext,j}^{od}$ ) accounts for the fact that transportation is associated with a number of negative externalities that are not compensated for, by the user fees and taxes. Notably, the absence of a market price for certain negative attributes of automobile mobility makes it difficult to compensate for their associated externalities. As a consequence, user fees and taxes fail to sufficiently cover the costs related to these negative externalities. Therefore, these costs are not fully internalized, leading to market inefficiencies and sub-optimal resource allocation. Consequently, the external cost was incorporated while estimating the generalized system cost for the integrated scenarios so as to evaluate the social benefits achieved through the public transit integration.

$$f(c)_{ext,j}^{od} = \sum_m^M [\gamma_{j,m}^{ext} \times d_{j,m}] \quad \forall j \in [1, 14] \quad (6)$$

where,

$\gamma_{j,m}^{ext}$  = External cost per unit distance for transit mode  $m$  in scenario  $j$

Eq. (6) describes the external costs for every scenario  $j$  for each origin destination pair ( $o, d$ ). The cost categories to be evaluated in this study were chosen based on the study's objective and are listed in Table 3 along with the corresponding values chosen for each mode.

**Generalized System Cost:** As already described, the generalized system cost ( $f(c)_{system,j}^{od}$ ) is the sum of the user, agency, and external costs. It takes into account how each scenario is performing in terms of their perceived user cost, how much the agency must invest for the scenario, and the amount of externalities the scenario would cause. Since generalized system cost incorporates all three elements, this metric can be utilized to evaluate the performance of the integrated system as well, which will be explored further in this study. Eq. (7) describes the generalized system cost for every scenario  $j$  for each origin destination pair ( $o, d$ ).

$$f(c)_{system,j}^{od} = f(c)_{user,j}^{od} + f(c)_{agency,j}^{od} + f(c)_{ext,j}^{od} \quad \forall j \in [1, 14] \quad (7)$$

Among the different scenarios created for each user and for each origin destination pair, the preferred integration-strategy is considered to be that with the minimum generalized system cost. Additionally, it is important to note that all variable values can be adjusted and calibrated to suit different locations, ensuring their applicability to specific sites.



**Table 3**

External cost: Factors and values.

Source: Litman (2021).

Costs	TNC	DRT	FRT	Description
External crash costs	0.053	0.042	0.036	Damages to nonusers' property, lost income, and medical expenses that are not paid. Expenditures for emergency response and crash prevention.
Barrier effect	0.013	0.011	0.003	Refers to the delays, inconvenience, and inaccessibility that vehicular traffic imposes on active modes like walking, bicycling, etc
Air pollution	0.196	0.225	0.128	Cost of vehicular air pollutants including greenhouse gases, emission rates of various vehicles
Noise costs	0.011	0.008	0.007	Hedonic price surveys are used to figure out how much noise costs caused by vehicular noises Such as when the engine revs up, the tires hit the road, the car stops, the horn sounds, etc
Congestion costs	0.336	0.265	0.009	Costs of traffic congestion include delays, costs to run a car, stress caused by cars getting in each other's way The external costs are what a vehicle costs other drivers and transit riders
Traffic service costs	0.012	0.009	0.002	How much public services like law enforcement, emergency services, and street lighting cost. Most of these costs are paid for by general taxes, so they can be thought of as an external cost of vehicle travel.
Road facility external costs	0.020	0.021	0.005	Government spending on roads and walkways, and how these expenditures are divided among modes External costs are roadway expenses not covered by user fees (specific fuel taxes, car fees, and tolls).
External resource costs	0.036	0.038	0.026	Resource consumption external expenditures refer to a variety of costs that are not directly borne by consumers This comes from the production, import, and distribution of resources (mainly petroleum) used in the building and operation of transportation systems
Land use impact costs	0.064	0.050	0.000	Transportation decisions' economic, social, and environmental impacts on land use It describes different external costs of low-density, automobile-oriented development
Water pollution costs	0.013	0.011	0.002	Water pollution refers to the direct or indirect release of dangerous substances into surface or ground water. Changes in surface (streams and rivers) and groundwater flows are referred to as hydrologic effects.
Waste disposal costs	0.000	0.000	0.000	Automobiles generate numerous hazardous byproducts that might impose externalities. Before being recycled, many abandoned vehicles remain for years, and some must be disposed of at public expense
External parking costs	0.147	0.127	0.000	Most parking expenses are external They are partially borne by non-vehicle owners, resulting in higher taxes, rents, retail prices, and wages Also environmental costs such as increased storm water management costs, heat island effects, and lost greenspace.
Total external cost	0.901	0.808	0.217	(All table values in Dollars per Passenger Mile)

### 3.3. Assignment of integrated scenario

As shown in schematic model of trip assignment (Fig. 5), each origin and destination pair is defined to have two buffer regions: the walking-buffer and the FRT accessibility-buffer. The walking buffer is denoted by an area whose radius corresponds to the distance an agent is able to walk ( $d_w$ ) to access public transportation. While, the accessibility-buffer is defined by the accessibility-radius  $r_{acc}$ . Within this accessibility buffer, transit users search for FRT stops, and on-demand services to provide with feeder services (Aravind et al., 2024b, 2023). In this study, the accessibility-radius is defined as the 95th percentile distance between origin and nearest FRT stop of completed trips using existing on-demand services in the study area. It was assumed that FRT stops within this radius are assumed accessible via feeder services, expanding the accessibility zone for tripmakers beyond feasible walking distances.

#### 3.3.1. Simulation

As illustrated in the flow chart in Fig. 6, for every agent  $n$ , and for each origin destination pair  $(o, d)$ , the model generates a collection of integrated public transport scenarios  $S_j$  and corresponding to each scenario, the generalized system cost ( $f(c)^{od}$ ) will be estimated. All modes are simulated under the assumption that the agent will select the shortest route, with the exception of FRT, which adheres to the designated route. The simulation is initiated by estimating the distance ( $\Delta^{od}$ ) between the  $o$  and  $d$ . The study also makes the assumption that the agent searches for FRT stops in a circular pattern (symmetric around their origin and destination) and use the Manhattan distance (Dong et al., 2018; Long and Thill, 2015) for distance search rather than the Euclidean distance. The initial choice of whether the journey can be performed by walking alone is determined based on this distance. The agent's decision to walk is based on the criteria that the distance to the destination  $\Delta^{od}$  is less than 400 m (0.25 miles Mulley et al., 2018). If

this criterion is satisfied, all other scenarios are deemed irrelevant and thus disregarded, otherwise the agent completes the trip by choosing various mode combinations as defined in the 14 scenarios (Refer to Table 2). For simplicity, this study assumes that agents can complete their trip using a single mode of transport or a combination of modes with a maximum of two transfers.

**Non-Integrated Scenarios:** For trips that exceeds walking distance, there are four non-integrated scenarios for the agent to complete the trip. As discussed,  $S_{TNC}$ ,  $S_{DRT}$ ,  $S_{FRT}$  and  $S_{FRT^{Hyp}}$  are the non-integrated scenarios and are completed using a single mode. A major assumption for non-integrated scenarios, with the exception of  $S_{FRT}$ , is that all trips between all origin–destination pairs can be successfully completed using these scenarios. In contrast, the  $S_{FRT}$  scenario is possible only if FRT stops are available within the walking buffer of both origin and destination. Furthermore,  $S_{FRT^{Hyp}}$  assumes that a hypothetical FRT stop is available within the origin and destination's walking buffer. This scenario mimics a situation where public transit accessibility is 100%. The consideration of scenario  $S_{FRT^{Hyp}}$  allows us to compare the effectiveness of the integrated system with an ideal situation of 100% public transit accessibility. In the simulation framework, the agent will complete the trip for various ODs using all the non-integrated scenarios and estimate the generalized system cost.

**Integrated Scenarios:** The study defines four integration-strategies, resulting in 10 scenarios, each representing a coordinated multi-leg trip with different transportation modes. Every integrated scenario has specific characteristics that are listed in Table 2. There are possibility that a trip maker might prefer non FRT integration-strategies, such as just combining on-demand services for a specific origin–destination pair. This is especially relevant in suburban areas with sparse and infrequent FRT networks. In such scenarios, if a trip maker misses the FRT on their first leg, the integration of DRT and TNCs becomes a more appealing alternative. Considering this fact, in this study, we consider the non-FRT integration strategy  $INT_{DRT,TNC}$ , that is available for every OD.

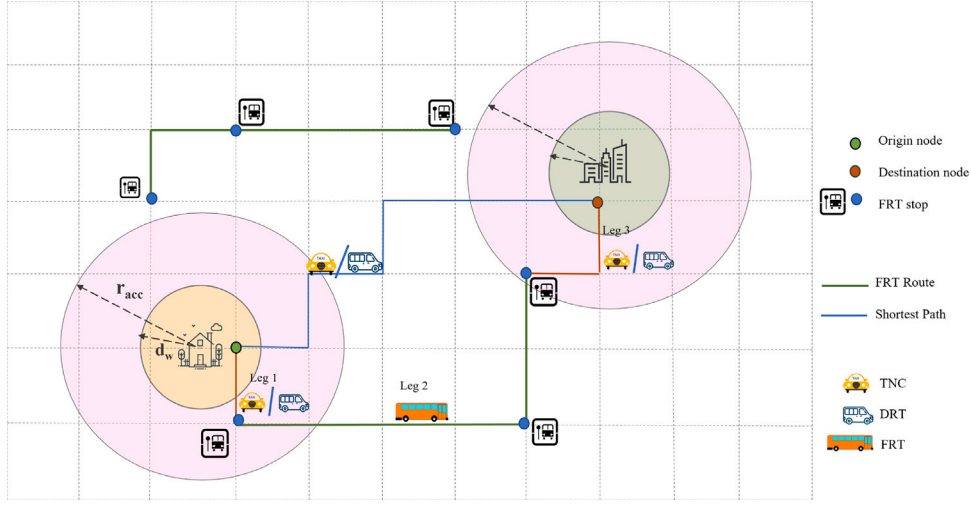


Fig. 5. Schematic diagram of trip assignment.

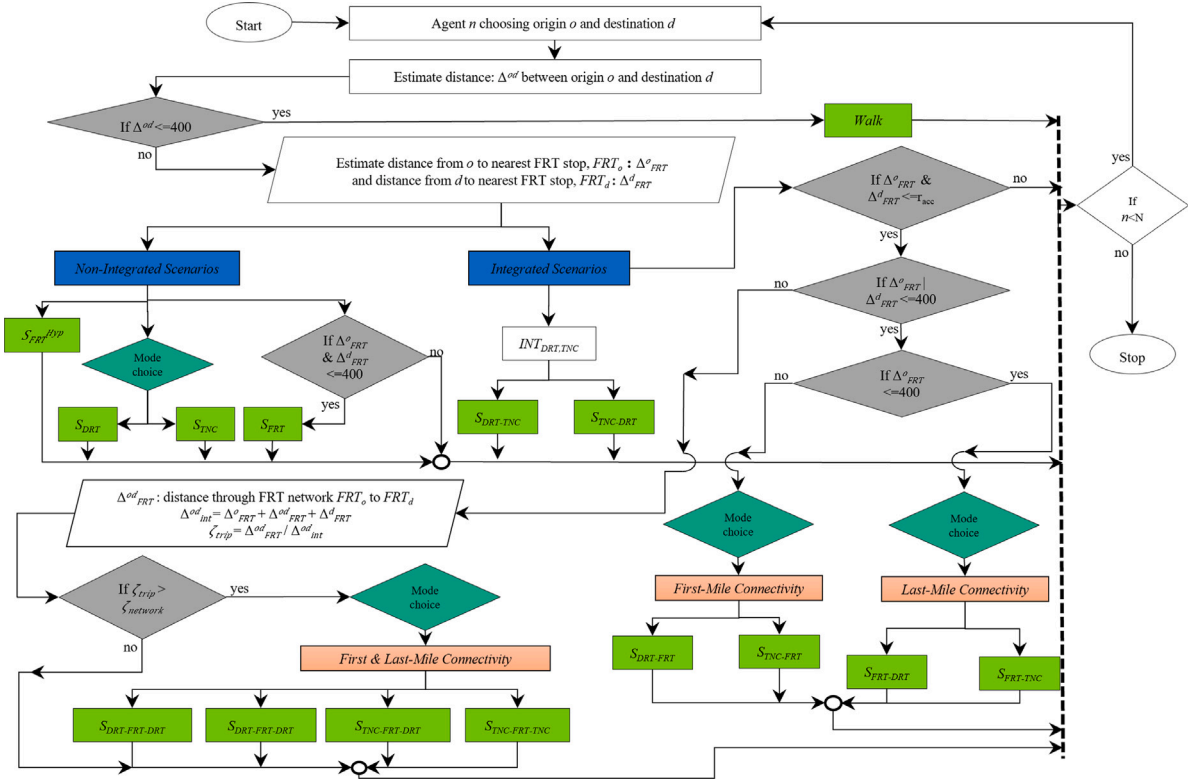


Fig. 6. Methodology for assignment of integrated scenario.

This integration-strategy has two legs, and each leg uses a different on-demand mode. Subsequently, there will be two scenarios  $S_{TNC-DRT}$  and  $S_{DRT-TNC}$ . As discussed, the transfer between the modes in this scenario happens at the nearest FRT stop, where the trip maker fails to be on time to board FRT. While the non-FRT scenarios might be appealing, integrating the FRT with on-demand services is of prime importance, which is crucial and beneficial.

This study examines two “2-modal” FRT integration-strategies:  $INT_{FRT,DRT}$ , and  $INT_{FRT,TNC}$  (using FRT and either one of the on-demand service). Both the integration-strategies have similar features except for the integrated mode. Within these integration, two-leg and three-leg scenarios are possible. In the two-leg scenarios, the on-demand service acts as a first-mile or last-mile connectivity service to FRT (they are,  $S_{DRT-FRT}$ ,  $S_{FRT-DRT}$ ,  $S_{TNC-FRT}$ , and  $S_{FRT-TNC}$ ).

In the three-leg scenario, both the FMLM connectivity services are provided by the same on-demand service (i.e.,  $S_{DRT-FRT-DRT}$  and  $S_{TNC-FRT-TNC}$ ). The simulation progresses in such a way that the agent searches for the nearest FRT stop for each OD pair and calculates the distance between them. Let  $\Delta^o_{FRT}$  is the distance between origin ( $o$ ) and the nearest FRT stop ( $FRT_o$ ), and  $\Delta^d_{FRT}$  be the distance between destination ( $d$ ) and the nearest FRT stop ( $FRT_d$ ).

All the scenarios listed above will occur if and only if it satisfy the following conditions. The scenario of on-demand service acting as a first-mile connection for FRT is when  $\Delta^o_{FRT}$  is less than FRT-accessibility-radius ( $r_{acc}$ ), and  $\Delta^d_{FRT}$  is less than the walking buffer. Similarly, on-demand service act as a last-mile connection for FRT if the  $\Delta^o_{FRT}$  is less than the walking buffer, and  $\Delta^d_{FRT}$  is less than FRT-accessibility-radius ( $r_{acc}$ ). The condition for the occurrence of the

three-legged scenario is when both  $\Delta_{FRT}^o$  and  $\Delta_{FRT}^d$  are less than the FRT accessibility-radius ( $r_{acc}$ ). This constraint ensures that both the origin and destination are located within the FRT accessibility-buffer of their nearest FRT stops. Therefore, the inclusion of the FRT leg in a trip can be assured using the criteria above.

Further, any integrated scenario with an FRT leg must be validated for its economic and operational feasibility. In this study, we assumed that the feasibility of on-demand services to provide both first-mile and last-mile connectivity to FRT depends on the transit coverage of a trip ( $\zeta_{trip}$ ). We also assumed that for a feasible FRT integration, the FRT coverage  $\zeta_{trip}$  must be greater than the transit coverage of the network ( $\zeta_{network}$ ). Here, the transit coverage of a trip or  $\zeta_{trip}$  is the ratio of the distance covered by FRT in the integrated scenario ( $\Delta_{FRT}^{od}$ ) to the total trip length of the integrated scenario ( $\Delta_{int}^{od}$ ). Whereas,  $\zeta_{network}$  is the ratio of the total length of FRT routes in the network to the total road length of the local road network under consideration. Mathematically, the transit and trip coverages are represented as follows:

$$\zeta_{network} = \frac{\|\mathcal{G}^{FRT}\|}{\|\mathcal{G}^{net}\|} \quad (8)$$

where,

$$\begin{aligned} \|\mathcal{G}^{FRT}\| &= \text{length of the total FRT network} \\ \|\mathcal{G}^{net}\| &= \text{length of the total routable network} \end{aligned}$$

$$\zeta_{trip} = \frac{\Delta_{FRT}^{od}}{\Delta_{int}^{od}} \quad (9)$$

where,

$$\Delta_{int}^{od} = \Delta_{FRT}^o + \Delta_{FRT}^{od} + \Delta_{FRT}^d \quad (10)$$

where,

$$\begin{aligned} \Delta_{FRT}^o &= \text{distance from origin } o \text{ to nearest FRT nodes, } FRT_o \\ \Delta_{FRT}^{od} &= \text{distance from } FRT_o \text{ to } FRT_d, \text{ through FRT network} \\ \Delta_{FRT}^d &= \text{distance from destination } d \text{ to nearest FRT nodes, } FRT_d \end{aligned}$$

If an on-demand mode serves as a FMLM feeder in a scenario, the  $\zeta_{trip}$  must be more than or equal to the  $\zeta_{network}$  for the scenario to be practicable as a feeder solution. Otherwise, the integrated scenario is not feasible and thus disregarded. Another integration strategy with FRT is the one that integrates all available modes i.e.,  $INT_{FRT,DRT,TNC}$  (3-modal integration-strategy). The possible scenarios within this integration strategy include  $S_{DRT-FRT-TNC}$  and  $S_{TNC-FRT-DRT}$ . Both of these scenarios are equivalent to the above-discussed three-legged scenarios which are  $S_{DRT-FRT-DRT}$  and  $S_{TNC-FRT-TNC}$ . The only obvious difference is that the mode for the first-mile and the last-mile connectivity is distinct.

### 3.4. Performance measures

Upon completion of the simulation of various scenarios and the determination of generalized system costs for the suggested scenarios, a comparative assessment is conducted to evaluate the relative competitiveness of different scenarios. There is a wide-range of measures used in literature to quantify accessibility. In this study, we adopt the Modal Accessibility Gap (MAG) to quantify the benefits of integration. MAG is an index as proposed by Kwok and Yeh (2004), which reflects the difference in accessibility offered by a pair of modes, normalized and bounded by  $[-1, +1]$ . We apply MAG index ( $MAG_i$ ) for different variables as shown as in Eq. (11).

$$MAG_i = \frac{X_i^{int} - X_i^{base}}{X_i^{int} + X_i^{base}} \quad (11)$$

where  $X$  can be the total travel time or generalized system cost to find the MAG values. The values of ( $MAG_i$ ) are equal to zero for trips that

have the same cost in both the base case scenario and the integrated scenarios. For trips where the integrated scenarios are considerably more competitive than the base case scenario, the values of ( $MAG_i$ ) approaches to  $-1$ . Conversely, for trips where the base case scenario is significantly more competitive than the integrated scenarios, the values of ( $MAG_i$ ) approaches to  $1$ .

## 4. Results and discussion

The ABM framework incorporates diverse components, each meticulously modeled based on the available dataset. Every parameter value utilized in the proposed model, such as headway, speed, cost, waiting time etc., can be adapted and transferred to different sites through appropriate calibration to ensure site-specific applicability. While the values in this study are tailored to a specific case, the model framework is flexible and transferable, allowing for customization to reflect the unique characteristics of different sites.

To ensure the realism and adaptability, key characteristics such as waiting times and fare distributions were derived from field data. The waiting time and the fare distribution for different modes were estimated from the field. The observed waiting times for TNC and DRT were modeled using various probability distributions such as the Gamma, Log-normal and Weibull and selected the best-fitting distribution. A comparison is made between the calibrated models using the Akaike information criterion (AIC) (Akaike, 1974) and the Bayesian information criterion (BIC) (Schwarz, 1978) statistics to determine the parameters of best fitting model. The model with relatively lower AIC or BIC values (Burnham and Anderson, 2004) was considered, which, for this study, was the lognormal distribution for DRT and Gamma distribution for TNC waiting time. Figs. 7(a) and 7(b) shows the various distribution fitted for DRT and TNC waiting times and Table 4 shows the distribution parameter values.

The average waiting time for DRT was found to be 11.6 min with a standard deviation of 9.53 min, whereas for TNC it was 13.5 min with a standard deviation of 3.73 min. The waiting time of DRT is lower than that of TNC because the DRT data used was prebooked, and was able to maintain a reliable operating characteristics. As for the FRT system, we assumed high-frequency operations, eliminating the need for passengers to synchronize their arrivals with vehicle times. As a result, the average traveler wait time was anticipated to be half the headway of FRT (Daganzo, 2010; Nourbakhsh and Ouyang, 2012). Moreover, as the FRT follows a fixed schedule, the variance in waiting time was assumed to be small in accordance with a standard assumption in this field (Sadriani et al., 2022; Gkiotsalitis and Cats, 2018; Avineri, 2004). Fig. 7(c) shows the waiting time distributions considered in the simulation framework for each mode.

To comprehend TNC pricing, the field data guided a bi-linear model (Fig. 7(d)) and the calibration yielded a base TNC fare of \$6.77 up to 3.22 miles; beyond this, fare increased linearly with distance ( $d_{TNC}$ ). Eq. (12) depicts the calibrated model. For DRT, a flat fare of \$3 was charged regardless of distance traveled when used as a feeder system to FRT. Otherwise, the DRT fare is considered as the penalized form of the TNC fare, with a penalty factor of 0.75. Furthermore, the FRT ticket system charges a one-time flat fare of \$1.5 irrespective of the distance traveled. Table 5 provides information regarding the trip fares, the average speeds of the vehicles, as well as the operating and running expenses of the different transportation modes that is adopted in the study. When transferred to a different study context, the values must be appropriately calibrated to account for site-specific characteristics. Considering the average operating and running cost, the values were chosen in dollar per passenger mile. This unit encapsulates costs across various factors, providing a granular measure that is easily comprehensible for both users and agencies. Moreover, it can be readily converted to other unit values. These derived values of cost, wait time, etc were subsequently employed in the ABM simulation.

$$\gamma_{TNC} = \begin{cases} 6.77, & \text{if } d_{TNC} \leq 3.22 \\ 1.3 \times d_{TNC} + 2.59, & \text{otherwise} \end{cases} \quad (12)$$

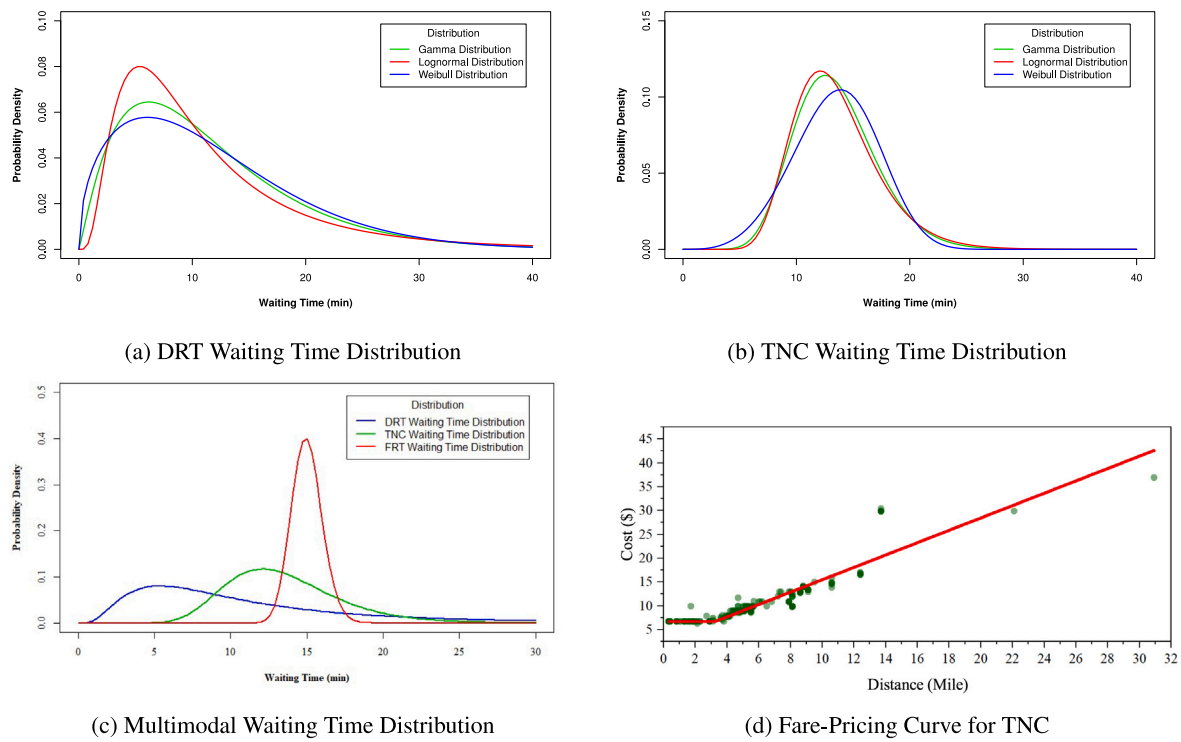


Fig. 7. Waiting time distributions and pricing curve considered in ABM.

Table 4

Parameters of waiting time distributions.

DRT waiting time distribution		Parameter			Log likelihood			AIC	BIC
Gamma distribution	Shape		Rate						
	Estimate	Standard error	Estimate	Standard error					
	2.13876	0.02259	0.18527	0.00220	−51 624.27			103 252.5	103 267.8
Log-normal distribution	Mean log		Std log						
	Estimate	Standard error	Estimate	Standard error					
	2.19450	0.00576	0.71886	0.00407	−51 203.9			102 411.8	102 427.1
Weibull distribution	Shape		Scale						
	Estimate	Standard error	Estimate	Standard error					
	1.48465	0.00900	12.86699	0.07357	−51 996.75			103 997.5	104 012.8
TNC waiting time distribution		Parameter			Log likelihood			AIC	BIC
Gamma distribution	Shape		Rate						
	Estimate	Standard error	Estimate	Standard error					
	14.06789	4.19223	1.04202	0.31612	−58.86164			121.7233	123.9054
Log-normal distribution	Mean log		Std log						
	Estimate	Standard error	Estimate	Standard error					
	2.56673	0.05783	0.27126	0.04089	−58.9816			121.9632	124.1453
Weibull distribution	Shape		Scale						
	Estimate	Standard error	Estimate	Standard error					
	4.10048	0.66703	14.87307	0.81862	−59.40624			122.8125	124.9946

Table 5

Parameter values for model application.

Values considered	FRT	DRT	TNC
Average speed (miles/h)	12 (Hughes-Cromwick, 2019)	15.2 (Hughes-Cromwick, 2019)	20 (Tarduno, 2021)
Fare (\$)	1.5 (ETHRA)	3 (ETHRA)	—
Average operating and running cost (\$/passenger mile)	1.31 (Federal Transit Administration)	4.37 (Federal Transit Administration)	1.31 (assumed)

#### 4.1. Numerical test - Sioux Falls

The well-known Sioux Falls network was used to assess the performance of the proposed integration model. The network, as depicted in Fig. 8, consists of 24 nodes and 38 bidirectional links. Three FRT routes are denoted by orange, green, and purple color arrows, and respectively representing FRT Route 1, FRT Route 2, and FRT Route 3. While all nodes represent potential user origins and destinations, nodes 10, 11, 14, 15, 4, 5, 22, 23, 16, 9 correspond to FRT stops. The FRT schedule is

designed to operate on a 30 min interval between 6 a.m. and 6 p.m. The network area was divided into income zones, namely: “Lower”, “Lower-Middle”, “Middle”, “Upper-Middle”, and “Higher” as shown as in Fig. 8. The travel demand was synthetically generated proportional to zone size, with income levels influencing the value of time for each trip. For each zone 1000 random demand were generated with a minimum allowable distance between them of 400 m, which is the maximum walking distance. Out of the random demand generated within each zone of income level, 1000 origin points were selected randomly and



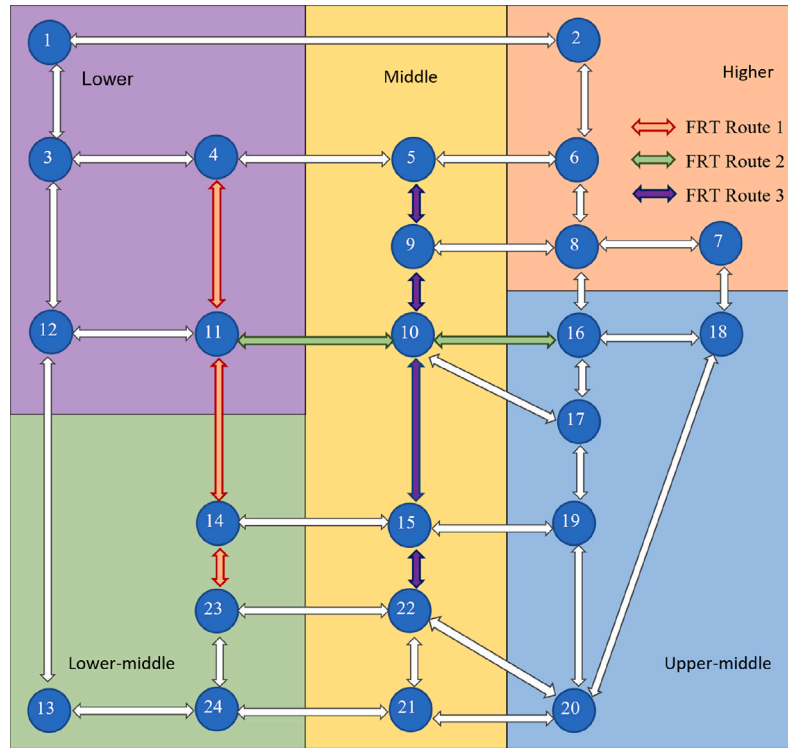


Fig. 8. Example network: Sioux Falls.

corresponding to each origin points 1000 destination points are selected to create 1000 O-D pairs. The study assumes that the traffic flow is operating at free flow conditions for Sioux Falls network.

#### 4.1.1. Computational results

Fig. 9 displays the generalized system cost distribution across different scenarios for trips from each zone. The  $S_{FRT^{Hyp}}$  scenario was considered as a base case scenario for a comparison of the cost of alternative scenarios. The results show that  $S_{FRT^{Hyp}}$  scenario gives the minimal generalized system cost for all O-D pairs. However, the feasibility of the  $S_{FRT^{Hyp}}$  scenario can be argued as establishing a complete fixed route to each origin and destination requires significant financial investment and is a time-consuming process. The results indicate that, the two-modal scenarios integrated to FRT generated comparable costs encouraging the use of on-demand services as feeders to FRT. Notably, the scenario with three mode combination generates an increased generalized system cost due to the multiple transfers and possible waiting time. In addition, when the VOT for the origin zone is high, the generalized system cost found to be lower for trips that are solely completed with on-demand services. This trend is also evident in the integration-strategy of on-demand services, like  $INT_{DRT,TNC}$ . This is due to the convenience the on-demand services offer, such as higher travel speed and shorter wait times, which persuades users to prefer them over comparing fare values alone. This results highlights the importance of incorporating VOT and convenience when designing and operating the public transportation systems to satisfy the needs of various user groups thereby minimize the overall costs.

**Time-space Diagram:** For a trip, there might be distinct routes for different scenarios. In order to highlight this, we analyzed an example trip for a particular O-D and presented how each scenario differs from each other in their course of journey by plotting the time-space diagram as shown in Fig. 10. The spatio-temporal representation of an example trip completed with the scenario  $S_{TNC-FRT-TNC}$  is shown in Fig. 10(a). This scenario, comprising three legs, involves TNC for initial pickup (waiting time: 7.1 min), followed by in-vehicle travel to the nearest FRT stop (3.6 min, 1.2 miles). Subsequently, the second leg involves

waiting for FRT (12.9 min) and FRT travel to the destination's nearest stop (14.4 min, 2.9 miles). The final leg consists of TNC's on-demand transit (waiting time: 9.1 min) and in-vehicle travel to the destination (6.4 min, 2.1 miles). The entire trip takes 53.4 min, covering a distance of 6.2 miles. Fig. 10(b) illustrates how other scenarios complete the same O-D, emphasizing the increase in travel duration with more legs. As a result, appropriate coordination is required to ensure the trip is completed with minimal disruptions and delays owing to the transitions between legs.

Fig. 11 illustrates the cost distribution for different scenarios completing the trip between the same O-D presented in Fig. 10. It shows that the lowest generalized system cost corresponding to this O-D is achieved for the scenario  $S_{TNC}$  with a total of 39.9\$ per user. However, at the same time, it has the highest external cost with 5.3\$ per user. According to the analysis, the scenario  $S_{TNC-DRT}$  had the highest generalized system cost of 104.3\$ per user. For the scenario  $S_{TNC-DRT}$ , this study assumes such a scenario occurs due to the failure of an FRT trip. At the initial leg, the trip maker travels to nearest the FRT stop using on-demand services, but fails to catch FRT and then decides to complete the service using another on-demand service. Therefore, the distance traveled here is larger than the shortest path, as it goes to the FRT stop first. Furthermore, from Fig. 11, it was also observed that the generalized system cost for the integration-strategies involving DRT is lower. This resulted from the use of a flat fare system for DRT when they are used as a feeder and this approach makes it less expensive than charging fares based on the distance traveled.

Fig. 12 presents the percentage of each scenario in completing the simulated overall trips. Among the total trips, 7% of them were completed by walking alone, whereas 93% were completed using the different possible scenarios. Out of this 93% of total trips that are greater than walking distance, 100% of them are possible to complete using scenarios  $S_{DRT}$ ,  $S_{TNC}$ , and also with the integration-strategy of  $INT_{DRT,TNC}$ .  $INT_{DRT,TNC}$  was again split as scenarios  $S_{DRT-TNC}$  and  $S_{TNC-DRT}$  covering 69% and 31% of trips, respectively. This suggests that all the trips can be accomplished by scenarios involving only on-demand services. However the motivation of integrated system is

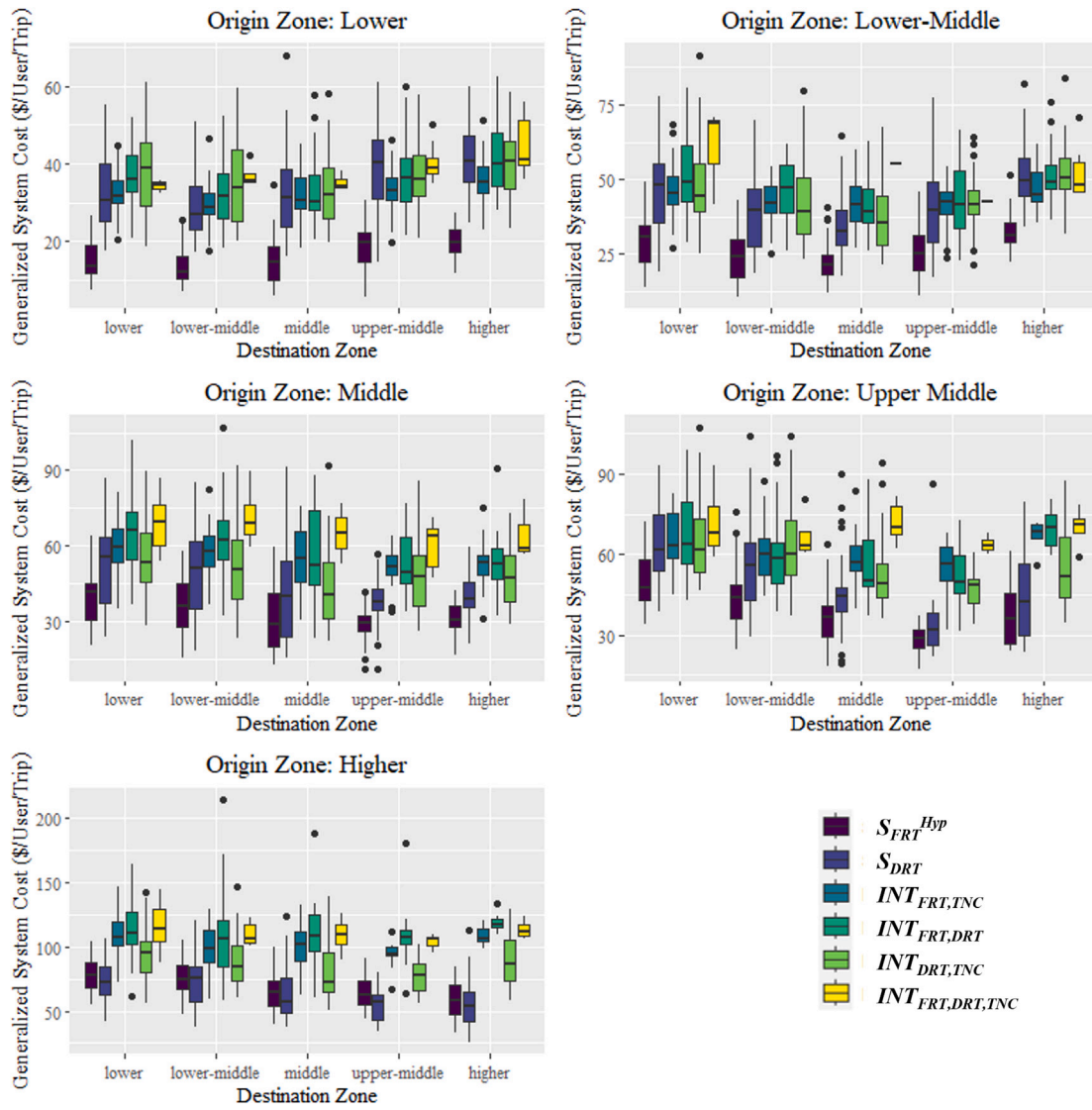


Fig. 9. Total system cost distribution for Sioux Falls.

to promote public transit system for a transit oriented development. Therefore, it is important that trips completed only through DRT, TNC, or their combination might not be promoted, but rather appropriately controlled.

The two-mode integration-strategies of  $INT_{FRT,TNC}$  and  $INT_{FRT,DRT}$  were able to accomplish 69% of the trips, and they were further segmented according to the order in which the modes are selected and the number of legs serving the trip. Out of the 69% of trips in this strategy, 61% were completed with  $S_{DRT-FRT-DRT}$  scenario, where DRT provides both first and last-mile connectivity. Further, 5% of the trips were accomplished using the scenario  $S_{FRT-DRT}$ , with DRT as the last-mile connectivity, and 3% were completed by  $S_{DRT-FRT}$  scenario, with DRT as the first-mile connectivity.

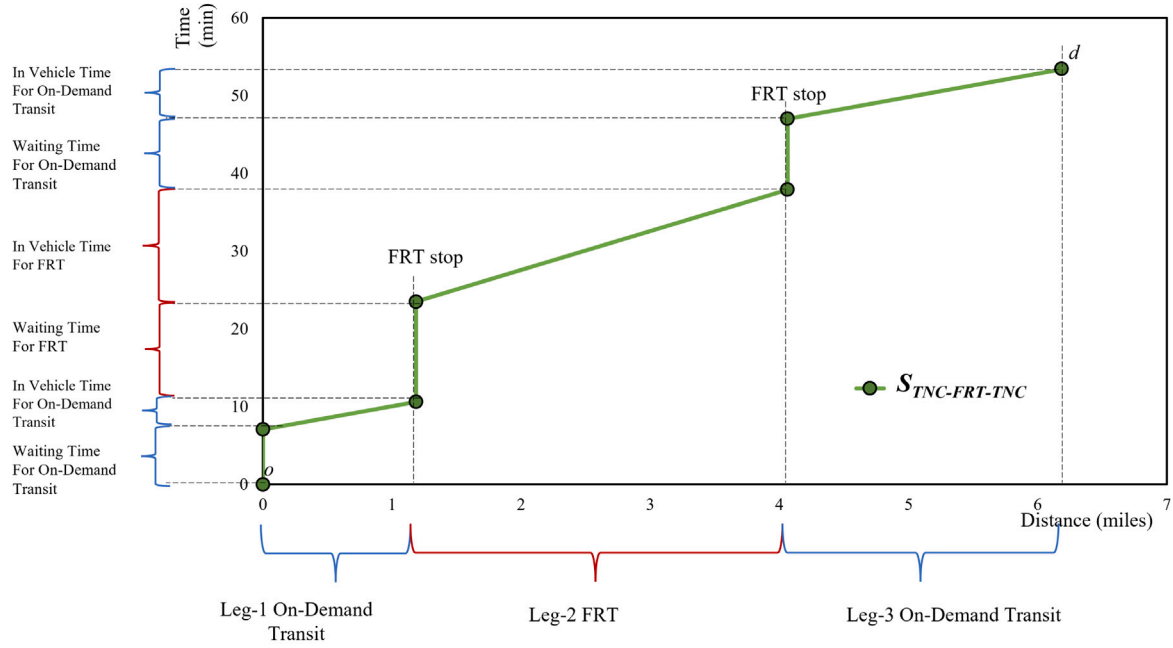
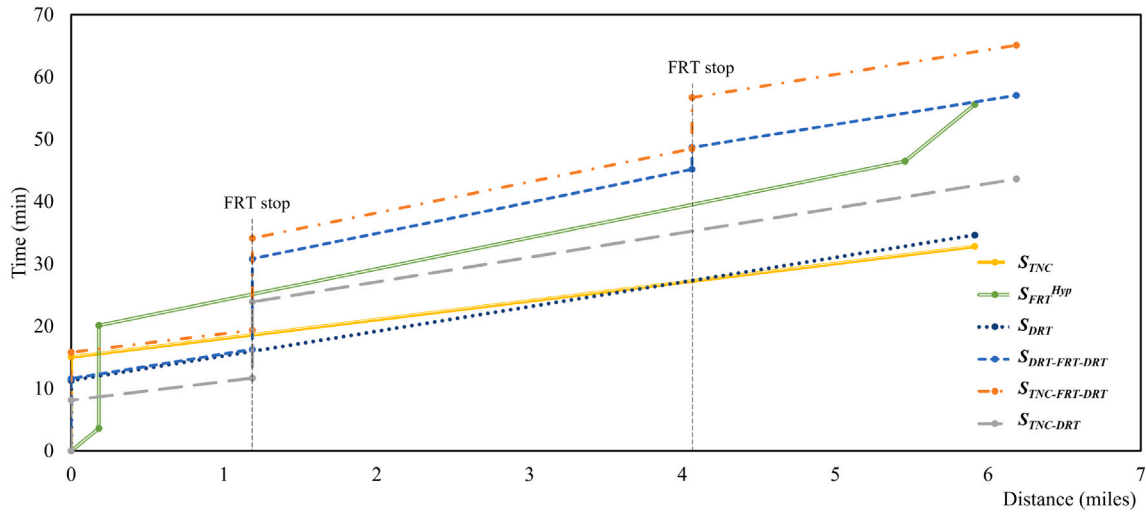
Essentially, there is a possibility to integrate 69% of the trips with FRT system with on-demand services acting as feeders. This indicates that 69% of trips met the criterion that the ratio between distance traveled in FRT and entire trip length is greater than the transit coverage of the area for the feeder solution to be economically viable. The results indicate that a substantial portion of the DRT and TNC services can effectively serve as a feeder to an integrated FRT system. However, while considering the integration-strategy  $INT_{FRT,DRT,TNC}$ , only 15% of the trips were attractive with this scenario as using multiple modes might not be as appealing due to coordination problems and the

associated delay. Therefore, more effective coordination strategies need to be devised and implemented, which is one of the vital future research scopes.

#### 4.1.2. Performance measures

In this section, we define the MAG index for different integration-strategies, where FRT serves a part of the trip, by comparing them to other scenarios where the trip is entirely served by on-demand service in a single-leg. This allows us to quantify the accessibility gap between the integrated and non-integrated strategies. The variables considered for the estimation of MAG values are user cost, agency cost, external cost, generalized system cost, and travel time.

Fig. 13 presents the MAG values for the preferred integration strategy for each O-D pair. As discussed, preferred integration-strategy to complete a trip between an origin destination pair was considered as the one with the minimum generalized system cost. Fig. 13a displays user cost MAG values with respect to on-demand scenario of  $S_{TNC}$ . By comparing user expenses to  $S_{TNC}$ , users can assess integrated scenarios compared to easily accessible private services. Additionally, the MAG values of agency cost were compared with the on-demand scenario  $S_{DRT}$ . This comparison is relevant as agencies are directly involved in operating the DRT service as opposed to TNC. The results show that, the preferred integration-strategy is more attractive from

(a) Distance-Time Diagram of an example O-D for the scenario  $S_{TNC-FRT-TNC}$  for Sioux Falls

(b) Distance-Time Diagram of an example O-D for different scenarios for Sioux Falls

Fig. 10. Time-space diagram for different scenarios of an Example O-D.

the agency's perspective ( $MAG < 0$ ) for the vast majority of trips. When comparing user costs, scenario  $S_{TNC}$  is more attractive than the preferred integration-strategy, possibly due to TNCs having minimal journey time, emphasizing the role of VOT. Fig. 13b shows the MAG values of external cost with respect to the on-demand scenario of  $S_{TNC}$  and scenario  $S_{DRT}$ . While comparing the external costs of the preferred integration-strategy from both the perspective of scenario  $S_{TNC}$  and  $S_{DRT}$ , the MAG values are less than zero for most of the trips, indicating the integration-strategy is more preferable at the environmental and social fronts.

Fig. 13c depicts the MAG values of the generalized system cost of the preferred integration-strategy compared to  $S_{TNC}$  and  $S_{DRT}$ . The MAG values of preferred integration-strategy compared to DRT indicate that it is equally competitive in terms of generalized system cost. Whereas, comparing with  $S_{TNC}$ , the preferred integration-strategy is less favorable for the majority of trips. Fig. 13d shows the MAG values in terms

of the total travel time of the preferred integration-strategy compared to  $S_{TNC}$  and  $S_{DRT}$ . The integration-strategies take longer to travel due to several transfers, making them less competitive. Noting that, the reduced external cost associated with integrated trips holds significance for sustainability, enhancing the attractiveness of integration-strategies in terms of user cost and travel time by optimizing trip scheduling is crucial.

Furthermore, Fig. 14 presents the comparison of different integration-strategies based on their MAG values corresponding to different performance measures, keeping the on-demand scenarios of  $S_{DRT}$  and  $S_{TNC}$  as benchmark. Fig. 14a compares MAG values for various integration-strategies based on generalized system cost relative to  $S_{DRT}$ . It is evident from the figure that all integration-strategies except  $INT_{FRT,TNC}$  have MAG distribution closely symmetric to zero in terms their generalized system cost. However, the integration-strategy

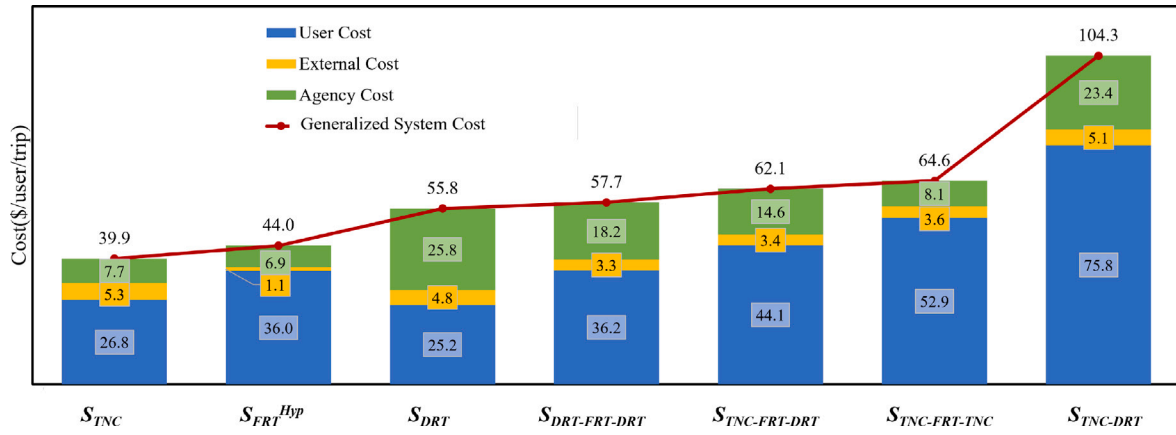


Fig. 11. Different cost factors for the multiple scenarios of the example O-D for Sioux Falls.

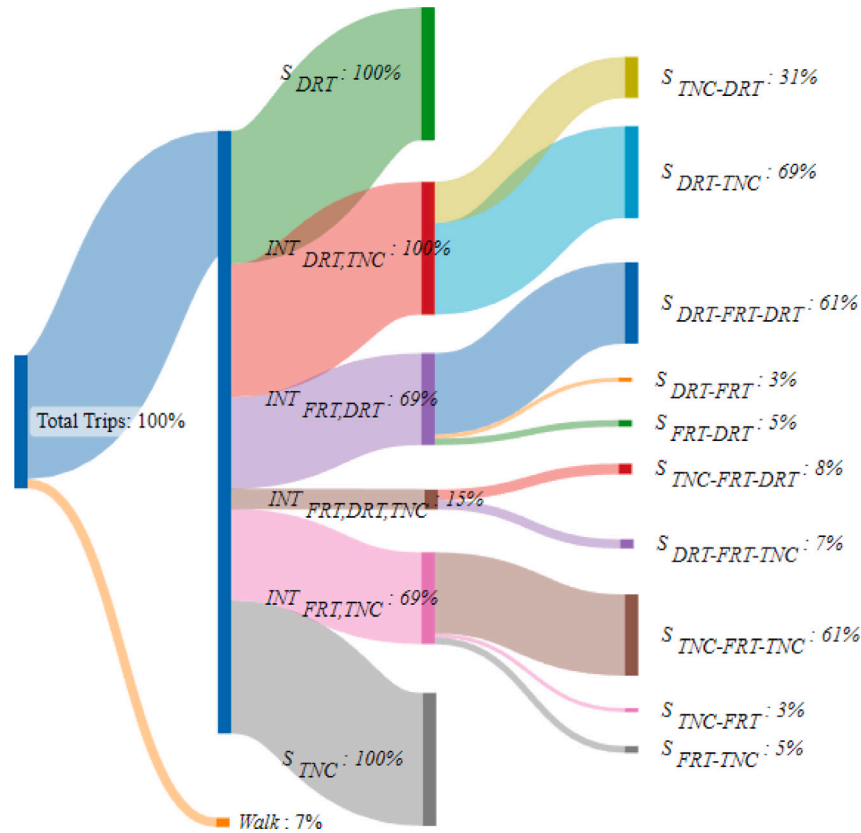


Fig. 12. Completed trips: Distribution of various integration scenarios for Sioux Falls.

$INT_{FRT,TNC}$  showed a significantly greater shift towards the positive side. This observation indicated that majority of the observed  $INT_{FRT,TNC}$  trips are less attractive compared to the on-demand only  $S_{DRT}$  alternative. Nonetheless, Fig. 14b shows that, when compared to the base scenario  $S_{TNC}$  in terms of generalized system cost, all scenarios shift positively, indicating  $S_{TNC}$  is more appealing, likely due to the convenience of a single-leg TNC trip. Consequently, these findings imply the necessity for a significant enhancement in the attributes of public transit and feeder systems to make them more attractive.

Fig. 14c and d is the comparison of different integration-strategies based on their MAG values in terms of the total travel times. The base for comparison is the on-demand scenarios of  $S_{DRT}$  (Fig. 14c) and  $S_{TNC}$  (Fig. 14d). The shift to positive side of all the scenarios, indicates increased travel times due to intermediate transfers in

integration-strategies, impacting competitiveness when compared to on-demand only scenarios. In Fig. 14e and f, MAG values for external cost are compared against  $S_{DRT}$  and  $S_{TNC}$ . It can be seen that all of the integration-strategies are more competitive compared to the on-demand alone scenarios. This implies that integrating with FRT proves advantageous in addressing external cost variables, thus contributing positively to societal and environmental well-being.

#### 4.2. Case study - Morristown City, Tennessee

The integrated strategies developed were also applied to a real network in Morristown City, Tennessee, United States, with a population of 30,431 residents (Census-Bureau, 2020). Fig. 15 displays the Morristown region, its adjacent zip codes, encompassing nine zip code zones, and FRT network. The network has 8888 nodes, 26,356



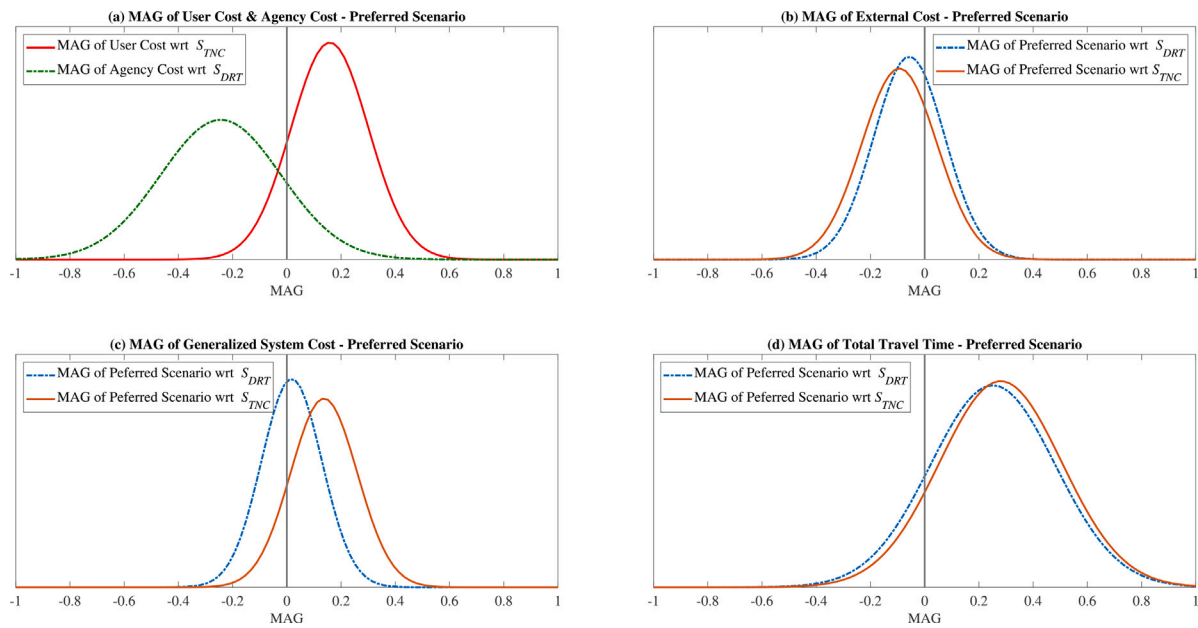


Fig. 13. MAG values of preferred integration-strategies for Sioux Falls.

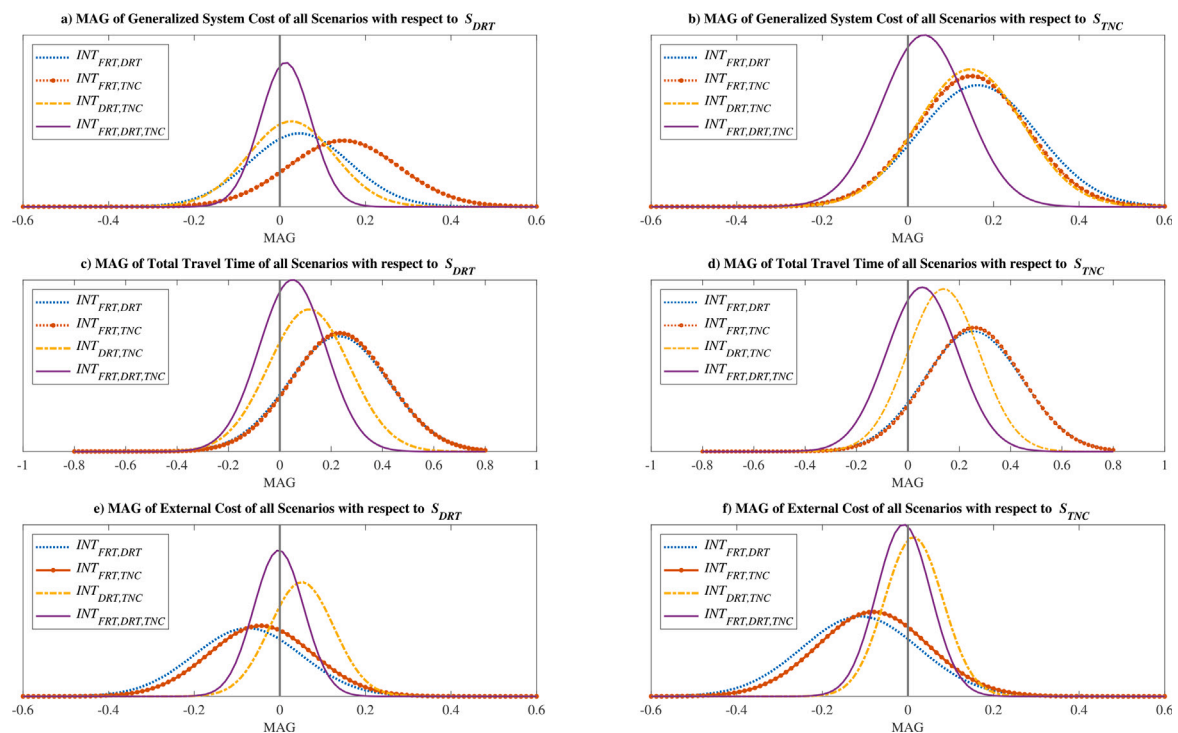


Fig. 14. MAG values of different integration-strategies for Sioux Falls.

links, and the city recently began operating FRT services with three distinct routes and 29 stops (as of the data collection date: May, 2020) and already operational DRT service. All the routes operates on a 30 min interval schedule between 6 a.m and 6.00 p.m. The existing FRT coverage is limited, primarily serving only two zip codes. Utilizing GTFS data, DRT trip characteristics, the study analyzed 381 unique O-D pairings, totaling 27,906 trips. Fig. 16 visually represents trip origins and destinations, emphasizing the highest demand between zip codes 37814-Morristown and 37813-Lowland. The network graph models for the study area were created considering the whole routable local road network, the FRT network, along with the zones based on zip codes. It is to be noted that, given the rural setting of the study area, the traffic was

primarily operating at a sub-capacity condition. Therefore, all modes considered in this study were traversing at the free-flow speed. After simulating the scenarios, by providing the first-mile or the last-mile connectivity, or both, 73% of trips could be successfully completed using the integration strategies.

**Preferred Integration-Strategy:** When it comes to integrated systems, the one with the lowest generalized system cost, will be selected as the preferred integration-strategy. The aggregated origin–destination (O-D) matrix of trips between zip codes, obtained upon completion of the simulation, is presented in Table 6a. Additionally, Table 6b displays the average O-D distance of the simulated trips. The matrix shown in Table 7 corresponds to the zip code based O-D matrix and indicates

**Table 6**  
Simulated zip code O-D matrix and distance matrix <sup>\*</sup> = FRT network available

(a) Simulated O-D Matrix								
O/D (Zipcode, Name)	37711 Bulls Gap	37760 Jefferson City	37813 Lowland*	37814 Morristown*	37820 NewMarket	37877 Talbot	37890 Banebury	37891 Whitesburg
37760 Jefferson City	-	1352	964	1556	1104	59	172	-
37813 Lowland*	18	1072	22843	33882	136	1548	3150	960
37814 Morristown*	4	2476	37302	40751	624	1848	1177	828
37860 Russellville	-	8	1328	566	4	-	-	4
37877 Talbot	-	102	1448	1552	138	44	8	-
37891 Whitesburg	-	-	28	28	-	-	-	-
(b) O-D Average Distance (Miles)								
O/D (Zipcode, Name)	37711 Bulls Gap	37760 Jefferson City	37813 Lowland*	37814 Morristown*	37820 NewMarket	37877 Talbot	37890 Banebury	37891 Whitesburg
37760 Jefferson City	-	11.7	13.9	12.6	17.1	15.2	18.5	-
37813 Lowland*	386	13.6	2.7	3.3	18.4	9.8	7.3	9.7
37814 Morristown*	11.9	12.4	3.7	3.5	17.7	7.8	5.5	10.0
37860 Russellville	-	18	9.1	6.7	21.4	-	-	3.5
37877 Talbot	-	17.6	9.4	7.4	11	3	9.7	-
37891 Whitesburg	-	-	8.3	8.6	-	-	-	-

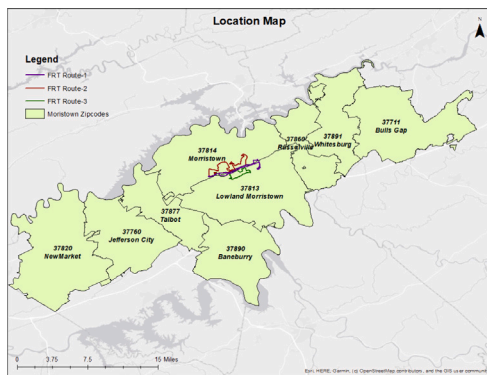
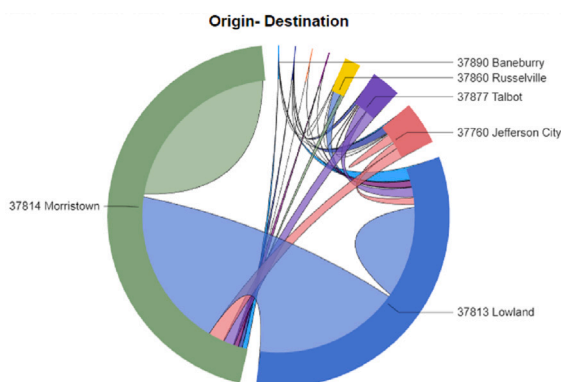


Fig. 15. Zipcode map of Morristown.



**Fig. 16.** Morristown: O-D demand.

which integration-strategy favored as preferred in each of these zip code zones. Once various integration-strategies have been formulated for each origin–destination pairs, the cells representing these strategies were visually distinguished by assigning color codes to specify the most preferred integration-strategy, out of the available options.

For example, the second-highest number of trips (33,882) occurs between Morristown (37 814) and Lowland-Morristown (37 813), and the preferred integration-strategy for O-Ds from these zip codes is

$INT_{FRT,DRT}$ . This indicates that users prefer to choose this integration-strategy probably due to its overall low generalized system cost and convenience. It can also be observed that wherever the FRT network was available, users preferred to include FRT in their trip. It is noteworthy that among all the integration-strategies, only  $INT_{DRT,TNC}$  was available for the rest of the O-Ds as evident from Table 7. It can be inferred that relying solely on integration-strategies may not be enough to achieve optimal transit accessibility, even though it enhances the existing FRT system. This is especially true when fixed routes and schedules are insufficient for convenient public transportation.

## 5. Summary and conclusion

Integration of conventional fixed transit systems with on-demand services, as well as the development of a hybrid public transit system, is a future requirement since more people must be attracted to public transportation to build a sustainable environment. In this study, we formulated a support tool for decision process of travel mode integration, powered by agent-based simulation to generate alternative possible integration-strategies between the public transit (FRT) and feeder services (DRT and TNC) for the completion of a trip and calculated the different cost factors for each of these scenarios. In this regard, we explored the perspectives of both users, and agencies, incorporating the external factors associated with the trip made using various integrated scenarios. The cost corresponding to each integrated scenario was estimated considering both monetary and non-monetary components. Monetary components consisted of fares, while non-monetary factors included considerations such as travel time and external factor costs. With the performance evaluation utilizing the MAG index, we analyzed the significance of various cost elements in each scenario. In conclusion, the research findings highlight the crucial factors that needs to be considered while integrating fixed and on-demand transit services to achieve optimal transit accessibility. The key conclusions, drawn from this study can be summarized as follows:

- i The majority of trips can be connected with the existing fixed-route transit network, if appropriately identified the integration strategy, highlighting the importance of providing FMLM connectivity. The proposed simulation framework could identify the best integration strategy that could connect 69% of trips in the Sioux Falls network and 73% of trips in the Morristown network with the existing FRT network.

**Table 7**  
Preferred integration-strategy for zip code O-D \* = FRT network available.

Preferred Scenario								
O/D (Zipcode, Name)	37711 Bulls Gap	37760 Jefferson City	37813 Lowland*	37814 Morristown*	37820 NewMarket	37877 Talbot	37890 Banebury	37891 Whitesburg
37760 Jefferson City	-	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$	-
37813 Lowland*	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$	$INT_{FRT,DRT}$	$INT_{FRT,DRT}$	$INT_{DRT,TNC}$	$INT_{FRT,DRT}$	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$
37814 Morristown*	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$	$INT_{FRT,DRT}$	$INT_{FRT,DRT}$	$INT_{DRT,TNC}$	$INT_{FRT,DRT}$	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$
37860 Russelville	-	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$	$INT_{FRT,TNC}$	$INT_{DRT,TNC}$	-	-	$INT_{DRT,TNC}$
37877 Talbot	-	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$	-
37891 Whitesburg	-	-	$INT_{DRT,TNC}$	$INT_{DRT,TNC}$	-	-	-	-

- ii Generalized system cost analysis in the proposed simulation framework emphasized the importance of considering the value of time and convenience when building and executing transportation systems to satisfy the needs of various user groups while minimizing costs. The viability of a specific scenario for a particular origin–destination pair cannot be deemed constant at all times. Various parameters, particularly the user's value of time, significantly influence the determination of feasibility.
- iii Wherever the FRT network was available, the preferred integration-strategy tended to be the integration scenario with an FRT leg. Therefore, in order to achieve an economically viable integration, the existing FRT network must possess a minimum coverage of fixed routes to ensure accessibility to maximum number of trips.
- iv The analysis conducted in this study revealed that the external cost of integrated trips is lower, highlighting the importance of accounting for sustainability when considering transportation options. While on-demand scenarios often outperformed integration-strategies in terms of travel time and user cost, the consideration of external costs made integration-strategies more attractive. Therefore, agencies need to consider diverse solutions for reducing user costs and agency costs associated with the efficient integration of fixed and on-demand transit services.

These research findings have shed light on the future scope of analysis and research in the field of public transportation. Specifically, the three-modal integration-strategy ( $INT_{FRT,DRT,TNC}$ ) has revealed that only a mere 15% of the trips were feasible through this strategy, and the travel duration for a single trip becomes significantly longer as the number of legs increases. Hence, further research is required to address the coordination problems that may arise while using multiple modes and legs and to ensure that the trip is completed with minimal disruptions and delays due to transitions between legs. To improve the viability and attractiveness of the integration-strategy with TNCs, public agencies can consider providing incentives on TNC operating costs and fares for users. This approach can promote collaboration between TNCs and public agencies and ultimately promoting transit oriented development. Additionally, the study highlights the inadequacy of fixed routes and schedules for facilitating convenient public transportation. Therefore, relying solely on integration-strategies may not be sufficient for achieving optimal transit accessibility in an area. Nevertheless, the knowledge gained from this study can be used to locate new FRT transit stops and routes, which can help improve public transit accessibility.

The application of the proposed simulation model can be calibrated against study region specific parameters to replicate the field scenario in the simulation model. As expected, a lower headway FRT system with extensive network coverage would result in a more FRT centric integrated multimodal transit system, where FRT will be one of the legs for most of the trips. As seen in the simulation model settings, the model inputs such as, FRT network configuration, number of FRT stops, and the frequency of FRT operations are some of the site-specific features that impact the modal integration scenarios and the associated

optimal system cost. This sensitivity of the simulation model towards the site-specific features ensures the transferability of the proposed simulation model. Therefore, the proposed model can be deployed at different cities with appropriate site-specific calibrations for a reliable cost estimation of various integration strategies.

It is important to recognize that an individual trip maker may perceive non integrated trips as more appealing, especially in suburban regions where the coverage and frequency of FRT networks are limited. In such cases, travelers may perceive direct trips involving DRT and TNCs, either combined or individually, as more favorable. However, it is crucial to take into account the requirements and preferences of all stakeholders when implementing a multimodal public transit system. In summary, while integration-strategies can enhance the existing fixed-route transit system, they may not be sufficient for achieving optimal transit accessibility in an area. Therefore, agencies need to consider diverse solutions for reducing the generalized system cost associated with the efficient integration of fixed and on-demand transit services, with the goal of providing convenient and sustainable public transportation for all. The most desirable scenario is the outcome of a better trade-off between several factors like VOT, trip time, vehicle operating cost, minimum fares, travel time reliability of the mode, transfer time, etc. It is essential to investigate these factors further to propose this method as a fully fledged, large-scale, optimal implementation strategy to build a more equitable public transportation system.

### 5.1. Limitations and future scope

This study presents a simplified modeling approach to evaluate the feasibility and effectiveness of integrated transportation systems at the pre-implementation stage, providing insights for informed investment planning. However, the study has certain limitations and must be acknowledged. The analysis assumes that all services are available at all times and our research assesses the economic benefits of the proposed mobility system only when transit authorities, DRT operators, and TNC service providers coordinate and work towards this shared goal, which may not always be the case in reality. It is therefore essential to investigate potential incentive mechanisms and policy options for non-cooperative settings.

Additionally, while this study indirectly captures TNC supply–demand imbalances through surge pricing, it does not explicitly model limited TNC supply across different cities. This simplification may overlook regional variations in service availability, impacting the accuracy of waiting time estimations. Future research could explore the impact of TNC service supply variability and its impact on modal integration that further enhances the realism of the simulation. Another limitation is that the study relies on external cost values derived from established references rather than real-data calibration, this may pose challenges for the transferability of the simulation model.

A further area for future research involves the investigation of congestion impacts. Congestion impacts are generally similar across modes for a given O-D pair, unless priority lanes are implemented. Incorporating scenarios that introduce an additional reward for the

FRT mode based on congestion levels could further refine the model. Moreover, identifying congestion-related costs and integrating them into the model as user convenience costs could allow agencies to develop operational policies that support a shift towards sustainable transportation modes.

### CRedit authorship contribution statement

**Avani Aravind:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Validation, Software, Formal analysis, Data curation, Conceptualization. **Suvini P. Venkureshiyil:** Writing – review & editing, Investigation, Methodology, Formal analysis, Data curation. **Sabya Mishra:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Candace Brakewood:** Writing – review & editing, Supervision, Investigation, Funding acquisition.

### Declaration of competing interest

None.

### Acknowledgment

This research is funded by the Tennessee Department of Transportation (Grant #RES-2021-03), the National Science Foundation (Grant #2431415), and the Center for Transportation Innovations Education and Research (C-TIER) at the University of Memphis. The opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the funding agencies.

### Data availability

The authors do not have permission to share data.

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