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Multi-objective optimization of integrated freight and passenger transportation in shared autonomous vehicle systems

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Abstract Recent urbanization and growing e-commerce have ignited freight demand, resulting in transportation challenges such as traffic congestion. A promising solution to the growing freight demand is integrating freight and passenger transportation to reduce the required number of vehicles. Shared Autonomous Vehicle (SAV) systems can efficiently integrate freight and passenger flows by using optimized routes and ride-sharing. Not only vehicle-based integration but also freight-passenger integration in urban spaces such as shared delivery locations (SDLs) such as lockers, would further enhance the performance of the integrated transportation system. The difference in time value between freight and passengers requires us to operate and design integrated transportation systems while explicitly evaluating trade-off relations between passenger convenience and social costs. This paper proposes a multi-objective optimization problem for integrated transportation in SAV systems that captures the dynamic features such as endogenous congestion and ride-share matching of freight and passengers. The optimization model is formulated as a linear programming, allowing us to easily solve it and mathematically derive useful properties for strategic planning. Our numerical experiments with New York City taxi data reveal that the employment of integrated transportation and SDLs synergistically improve passenger convenience and social costs simultaneously.

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1 Introduction

1.1 Background

Recent trends such as urbanization and the e-commerce boom have boosted the demand for urban freight deliveries [14], posing transportation challenges such as congestion [18]. The prevalence of e-commerce has invited customers to purchase goods online and have them delivered directly to their desired locations (e.g., homes and workplaces). However, compared to classical delivery to shops, direct delivery requires visits to geographically dispersed locations, putting further pressure on transportation infrastructures due to the increased number of vehicles and mileage [1]. The future growth of the e-commerce market will force us to formulate freight transportation solutions to alleviate the negative impacts on urban transportation.

A promising solution to the urban transportation challenges owing to growing freight demand is to integrate freight and passenger transportation. According to Bruzzone et al. [3], an integrated system includes vehicles, infrastructures, or urban spaces shared by freight and passengers simultaneously. The European Green Paper on Urban Mobility [5] indicated the necessity of integrated transportation, which has since been successfully implemented in long-haul transportation [7] and fixed-route public transit [13]. In contrast, in the context of short-haul transportation in urban road networks, freight and passenger flows compete over limited spaces, as seen in dedicated ride-hailing services (e.g., UberPool and UberEats). The unique features of short-haul transportation require congestion-aware operation of flexible vehicle routing and scheduling.

Shared autonomous vehicle (SAV) systems present a high potential for integrated freight and passenger transportation in urban road networks. SAV systems utilize autonomous vehicles shared by society to transport them using optimal routes, schedules, and ride-sharing matching [17]. This allows a single vehicle to efficiently carry heterogeneous overlapping flows, thereby reducing the number of vehicles required to meet the same traffic demand. According to Joerss et al. [9], autonomous vehicles with parcel lockers will likely cover 80% of last-mile deliveries in the future.

The integrated transportation system would bring greater social benefits if freight and passenger flows could be shared not only in vehicles but also in urban spaces such as transport hubs. Transport hubs that have recently gained attention in the context of freight transportation are shared delivery locations (SDLs), such as parcel lockers and shops [18]. Freight is delivered from warehouses to SDLs, rather than to each customer's home or workplace, where it is stored as inventory and eventually picked up by the customer who ordered them. The system with SDLs can provide the following two advantages [1,18]. First, consolidating freight destinations and passenger transit points at SDLs can provide an opportunity to increase the vehicle loading rate. Second, it avoids magnifying congestion by storing freight at SDLs during off-peak traffic demand.

The operation and design of the integrated transportation system require us to explicitly investigate the trade-off relations between passenger convenience and social costs [3]. Passenger convenience includes total travel time, whereas social cost includes total distance traveled by SAVs, total number of SAVs, infrastructure construction costs, and total inventories. For example, delivering to SDLs rather than customers' homes could reduce vehicle travel distances at the expense of passenger travel time. Holding more inventories at SDLs during off-peak demand could also avoid traffic congestion. Similar to typical transportation systems, there exist strong trade-off relations between construction costs and travel time. Furthermore, the difference in time value of freight and passengers highlights the importance of the trade-off relations in the operation and design of integrated transportation systems.

1.2 Literature Review

Many papers researchers have focused on the integration of freight and passenger transportation since the publication of the European Green Paper [5]. Related studies can be roughly classified into two categories: those focusing on fixed-routes public transits (e.g., rail [16]), and short-haul transportation with flexible routes, such as taxis [12], on-demand buses [4], and SAVs [2, 20]. This study is highly related to the latter.

Most previous studies on integrated transportation with flexible routes have been concerned with optimizing operational routing and scheduling, with fewer contributions to strategic design. Li et al. [12] formulated a variant of the Dial-a-Ride problem to optimize routes and schedules of taxis such that satisfy two types of traffic demand (i.e., passenger and freight). Cheng et al. [4] proposed an integrated transportation model in demand-responsive bus systems with drones. Beirigo et al. [2] developed an integrated transportation model in SAV systems by relaxing the assumptions on the combination of freight and passengers in [12]. They revealed that integrated transportation performs on average 11% better than conventional one.

To our best knowledge, only two studies, Van et al. [20] and Ji et al. [8], have investigated strategic issues for integrated transportation with flexible routes. Van et al. [20] provided the Dial-a-ride problem with SAVs' capacity design, an extension of [2]. Numerical experiments on a hypothetical network demonstrated that vehicle capacity design varies significantly with freight and passenger demand patterns. Ji et al. [8] formulated a mixed integer linear programming to explore the optimal routing and hub-and-spoke network design in multimodal transportation consisting of metro, taxi, and truck. Unfortunately, no studies have contributed to the integrated freight and passenger transportation with flexible routes while explicitly considering endogenous traffic congestion, the trade-off relations between passenger convenience and social costs, and the strategic design. These concerns must be evaluated in the operation and design of integrated transportation since the growing e-commerce would boost freight demand loading the urban infrastructures.

Traffic assignment approaches are typical methodologies for evaluating the interaction between traffic phenomena (e.g., congestion) and strategic network design. Its dynamic extension, a dynamic traffic assignment (DTA), can evaluate traffic congestion in SAV systems that require dynamic matching in response to spatio-temporal passenger demand. Since Levin [10] has formulated the SAV routing problem while considering endogenous congestion as linear programming, the DTA approach for SAV systems has focused on passenger transportation and incorporated public transit [11, 15] and infrastructure design [15,19]. Seo and Asakura [19] developed the multi-objective optimization framework, which simultaneously optimizes the dynamic operation and infrastructure design of SAV systems. Maruyama and Seo [15] extended [19] to SAV systems with fixed-route transits. This study extends [19] to the integrated freight and passenger transportation, and can be a first step toward developing a multi-objective optimization framework for congestion-aware strategic design and operation of the focused system.

1.3 Objective

This study develops a multi-objective optimization model for integrated freight and passenger transportation that evaluates trade-off relations and traffic congestion. The objective functions include total travel time of passengers, total distance traveled by SAVs, total number of SAVs, infrastructure construction cost, and total inventories. The proposed model employs a DTA approach to capture the dynamic features of integrated transportation in SAV systems: endogenous congestion, dynamic routing and scheduling of SAVs, storage of freight, and ride-sharing matching of freight and passengers. The model is formulated as linear programming; thus, we can solve it easily. Furthermore, leveraging the linearity of the problem can derive the following mathematical properties: the employment of integrated transportation and SDLs can improve passenger convenience and social costs simultaneously (i.e., Pareto improvement). Our numerical experiments clarify the trade-off relations, as well as the Pareto improvement produced synergistically by integrated transportation and SDLs.

2 Formulation

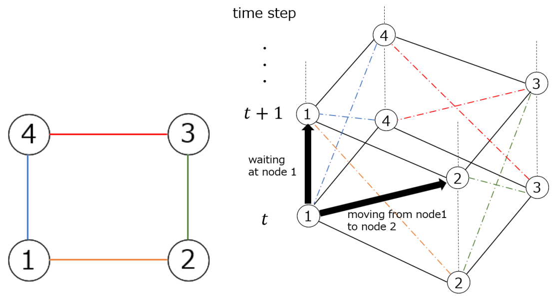
This chapter develops a multi-objective optimization model for integrated freight and passenger transportation. Section 2.1 explains the problem settings, Section 2.2 formulates the optimization model, Section 2.3 describes the solution method, and then Section 2.4 shows the qualitative properties. Finally, Section 2.5 describes the limitations of the proposed model.

2.1 Problem Settings

Integrated freight and passenger transportation system consists of five elements: network, passengers, freight, SAVs, and a decision-maker. The following sections describe the problem setting for each element.

2.1.1 Decision-maker

A decision-maker determines the routes and schedules of SAVs within a given planning horizon while designing



(a) standard network (b) time-expanded network

Fig. 1: An example of time-expanded network

the network required for efficient SAV operation. The system can transport freight and passengers along optimal routes while satisfying traffic and freight demand. The optimal operation and design minimize the total travel distance and the total number of SAVs, the total amount of freight in stock, the total cost of expanding infrastructure facilities such as parking lots, roads, and SDLs, and the total travel time of passengers.

2.1.2 Network

A network consists of nodes and links. There are two types of nodes: nodes on the road network and dummy nodes. The former represents parking lots and intersections, while the latter is an aggregated representation of origins, destinations, and facilities such as warehouses and SDLs in each zone. Each link has travel time and traffic capacity. The travel time is given, while traffic capacity is determined through network design along with the storage capacity of nodes on the road network. The traffic and storage capacity restrict the number of SAVs using the corresponding links and nodes. Facility dummy nodes have inventory capacity, the maximum number of freight stored. The capacities can be designed within a given maximum and minimum value.

This study considers a time-expanded network—a network that extends the static network along the time axis shown as Fig. 1. It describes movement and waiting and their time consumption. Passengers, freight, and SAVs all move on the time-expanded network.

2.1.3 Freight and Passenger

Passengers travel according to the optimal route directed by the decision-maker and eventually return to their destinations. They can move only when riding SAVs; otherwise, they must wait at a node. There are two types of passengers: with and without freight demand. Passengers with freight demand move to the destination after receiving their desired freight, while their counterparts move directly to the destination. Passengers can pick up the freight at the destination or SDLs.

Similar to passengers, freight is also carried exclusively by SAVs. If freight waits at a node, it must be stored at warehouses, SDLs, or SAVs. All freight to meet passengers' demand is pre-positioned at warehouses at the beginning of the planning horizon and then delivered to passengers within the planning horizon.

We assume that passenger demand during the planning horizon is given. Passenger demand is identified by origin, destination, departure time, latest arrival time, with or without freight demand, and volume and type of freight demand. For simplicity of notation, this study assumes the latter two components are homogeneous.

2.1.4 SAV

SAV flow is described by a point-queue model with a limited queue length. SAVs move on links at free-flow speed and stop at nodes when parked or in congestion. Congestion occurs when the traffic volume reaches the traffic capacity of links or the storage capacity of nodes. Then SAVs cannot enter the link or node, resulting in the propagation of traffic congestion. The dynamic representation of SAV flow is identical to that of [19].

SAVs follow the optimal itinerary and route directed by the decision-maker. SAVs can pick up passengers and carry freight subject to the pre-determined vehicle carrying capacity. This study refers to transportation systems in which each SAV can transport freight and passengers simultaneously as integrated transportation, otherwise referred to as separated transportation.

2.2 Optimization Problem

A multi-objective optimization problem for integrated transportation is formulated according to the problem settings described in Section 2.1. The definitions of variables and parameters are summarized in Table 1, 2 and 3, and the optimization problem is expressed as follows:

$$\min\{T, D, N, C, S\} \qquad \text{subject to} \tag{1}$$

$$\sum_{ij,k,s,t\in \boldsymbol{T}_k} t_{ij}(y^{k,t}_{s,ij} + \hat{y}^{k,t}_{s,ij} + \tilde{y}^{k,t}_{s,ij}) = T, \tag{2}$$

$$\sum_{ij\in \boldsymbol{E}, i\neq j,t} d_{ij}x^t_{ij} = D, \tag{3}$$

$$\sum_{i\in \boldsymbol{V}} x^0_{-1i} = N, \tag{4}$$

$$\sum_{ij\in \boldsymbol{E}} c_{ij}(\mu_{ij} - \mu^{\min}_{ij}) + \sum_{i\in \boldsymbol{V}} c_i(\kappa_i - \kappa^{\min}_i) + \sum_{v\in \boldsymbol{\mathcal{V}}^{\mathrm{W}}\cup\boldsymbol{\mathcal{V}}^{\mathrm{L}}} \hat{c}_v(\epsilon_v - \epsilon^{\min}_v) = C, \tag{5}$$

$$\sum_{t,v\in \boldsymbol{\mathcal{V}}^{\mathrm{W}}\cup\boldsymbol{\mathcal{V}}^{\mathrm{L}}} z^t_{vv} = S, \tag{6}$$

$$\sum_{j\in \boldsymbol{V}} x^{t-t_{ji}}_{ji} - \sum_{j\in \boldsymbol{V}} x^t_{ij} = 0 \qquad \forall i, t \in (0, t_{\max}), \tag{7}$$

$$\sum_j y^{k,t-t_{ji}}_{s,ji} - \sum_j y^{k,t}_{s,ij} + y^{k,t}_{s,-1i} - y^{k,t}_{s,i1} = 0 \qquad \forall i, s, k, t \in \boldsymbol{T}_k, \tag{8}$$

$$\sum_j \hat{y}^{k,t-t_{ji}}_{s,ji} - \sum_j \hat{y}^{k,t}_{s,ij} + \hat{y}^{k,t}_{s,-1i} - \hat{y}^{k,t}_{s,i0} = 0 \qquad \forall i, s, k, t \in \boldsymbol{T}_k, \tag{9}$$

$$\sum_j \tilde{y}^{k,t-t_{ji}}_{s,ji} - \sum_j \tilde{y}^{k,t}_{s,ij} + \tilde{y}^{k,t}_{s,0i} - \tilde{y}^{k,t}_{s,i1} = 0 \qquad \forall i, s, k, t \in \boldsymbol{T}_k, \tag{10}$$

$$\sum_j z^{t-t_{ji}}_{ji} - \sum_j z^t_{ij} + z^t_{-1i} - z^t_{i0} = 0 \qquad \forall i, t, \tag{11}$$

$$\sum_{s,k} y^{k,t}_{s,ij} + \sum_{s,k} \hat{y}^{k,t}_{s,ij} + \sum_{s,k} (\sigma+1)\tilde{y}^{k,t}_{s,ij} + \sigma z^t_{ij} \leq \rho x^t_{ij} \qquad \forall ij \in \boldsymbol{E}, i\neq j, t, \tag{12}$$

$$x^t_{ij} \leq \mu_{ij} \qquad \forall ij, i\neq j, t, \tag{13}$$

$$x^t_{ii} \leq \kappa_i \qquad \forall i, t, \tag{14}$$

$$\sigma z^t_{ii} \leq \rho x^t_{ii} \qquad \forall i \in \boldsymbol{V}, t, \tag{15}$$

$$z^t_{vv} \leq \epsilon_v \qquad \forall v \in \boldsymbol{\mathcal{V}}^{\mathrm{W}} \cup \boldsymbol{\mathcal{V}}^{\mathrm{L}}, t, \tag{16}$$

$$y^{k,k}_{s,-1r} = Y^k_{rs} \qquad \forall rs, k, \tag{17}$$

$$\sum_{t\in T_k} y^{k,t}_{s,s1} = \sum_r Y^k_{rs} \qquad \forall s, k, \tag{18}$$

$$\hat{y}^{k,k}_{s,-1r} = \hat{Y}^k_{rs} \qquad \forall rs, k, \tag{19}$$

$$\tilde{y}^{k,t}_{s,0v} = \hat{y}^{k,t}_{s,v0} \qquad \forall v \in \boldsymbol{\mathcal{V}}^{\mathrm{L}}_s, s, k, t \in T_k, \tag{20}$$

$$\sum_{v\in \boldsymbol{\mathcal{V}}^{\mathrm{L}}_s, t\in T_k} \hat{y}^{k,t}_{s,v0} = \sum_{t\in T_k} \tilde{y}^{k,t}_{s,s1} = \sum_r \hat{Y}^k_{rs} \qquad \forall s, k, \tag{21}$$

$$\sum_{v\in \boldsymbol{\mathcal{V}}^{\mathbf{W}}} z^0_{-1v} = \sum_{t,v\in \boldsymbol{\mathcal{V}}^{\mathrm{R}}} z^t_{v0} = \gamma \sum_{rs,k} \hat{Y}^k_{rs}, \tag{22}$$

$$z^t_{v0} = \gamma \sum_{k,s} \hat{y}^{k,t}_{s,v0} \qquad \forall v \in \boldsymbol{\mathcal{V}}^{\mathrm{R}}, t, \tag{23}$$

$$\mu^{\min}_{ij} \leq \mu_{ij} \leq \mu^{\max}_{ij} \qquad \forall ij \in \boldsymbol{E}, \tag{24}$$

$$\kappa^{\min}_i \leq \kappa_i \leq \kappa^{\max}_i \qquad \forall i \in \boldsymbol{V}, \tag{25}$$

$$\epsilon^{\min}_v \leq \epsilon_v \leq \epsilon^{\max}_v \qquad \forall v \in \boldsymbol{\mathcal{V}}^{\mathrm{W}} \cup \boldsymbol{\mathcal{V}}^{\mathrm{L}} \tag{26}$$

in combination with non-negative constraints.

Eq. (2)–(6) define the objective functions, Eq. (2) defines the total travel time of passengers, Eq. (3) defines the total distance traveled by SAVs, Eq. (4) defines the total number of SAVs, Eq. (5) defines the total infrastructure construction cost, and Eq. (6) defines the total inventories.

The conservation law at a node must be satisfied; the total inflow and outflow at a node must be equal. Eq. (7) represents the node conservation law of SAVs, Eq. (8)–(10) represent that of passengers without freight demand, with unserved freight demand, and with served freight demand, respectively, and Eq. (11) represents

Table 1: List of variable notation

notation	definition
x_{ij}^{t}	flow of SAVs that start traveling link ij on time step t
$y_{s,ij}^{k,t}$	flow of passengers who start traveling link ij on time step t with no freight demand, destination node s, and departure time step k
$\hat{y}_{s,ij}^{k,t}$	flow of passengers who start traveling link ij on time step t with unserved freight demand, destination node s, and departure time step k
$\tilde{y}_{s,ij}^{k,t}$	flow of passengers who start traveling link ij on time step t with served freight demand, destination node s, and departure time step k
z_{ij}^{t}	flow of freight that starts traveling link ij on time step t
T	total travel time of passengers (including waiting time on nodes)
D	total distance traveled by SAVs
N	total number of SAVs
C	total cost of infrastructure construction
S	total number of inventories
μ_{ij}	traffic capacity of link ij, which is within the minimum allowable value $\mu_{ij}^{\min}$ and the maximum allowable value $\mu_{ij}^{\max}$
κ_i	storage capacity of node i for SAVs, which is within the minimum allowable value $\kappa_i^{\min}$ and the maximum allowable value $\kappa_i^{\max}$
ϵ_v	storage capacity of facility dummy node v for freight, which is within the minimum allowable value $\epsilon_v^{\min}$ and the maximum allowable value $\epsilon_v^{\max}$

Table 2: List of parameter notation

notation	definition
t_{ij}	free-flow travel time of link ij if $i \neq j$
t_{ii}	waiting time at node i for one time step (i.e., equal to the time step width by the definition)
d_{ij}	length of link ij
c_{ij}	unit cost of expanding traffic capacity of link ij
c_i,$\hat{c}_v$	unit cost of expanding storage capacity of node i for SAVs and facility dummy node v for freight, respectively
ρ	carrying capacity of an SAV
σ	relative size of single freight against a single passenger
γ	volume of freight demand per passenger
Y_{rs}^{k}	time-dependent demand of passengers with no freight demand, origin r, destination s, and departure time step k
$\hat{Y}_{rs}^{k}$	time-dependent demand of passengers with freight demand, origin r, destination s, and departure time step k
$t_{\max}$	final time step

Table 3: List of set notation

notation	definition
$\boldsymbol{T}_k$	travel time window for passengers with departure time step k
$\boldsymbol{V}$, $\boldsymbol{E}$	sets of nodes and links on road network, respectively
$\boldsymbol{\mathcal{V}}^{\mathrm{W}}$,$\boldsymbol{\mathcal{V}}^{\mathrm{L}}$	sets of dummy nodes representing candidate warehouses and SDLs, respectively
$\boldsymbol{\mathcal{V}}_s^{\mathrm{L}}$	set of dummy nodes where passengers with destination node s can receive freight ($\boldsymbol{\mathcal{V}}_s^{\mathrm{L}} = \{\boldsymbol{\mathcal{V}}^{\mathrm{L}} \cup \{s\}\}$)
$\boldsymbol{\mathcal{V}}^{\mathrm{R}}$	set of all dummy nodes where passengers can receive freight (($\boldsymbol{\mathcal{V}}^{\mathrm{R}} = \{\boldsymbol{\mathcal{V}}_s^{\mathrm{L}} \mid \forall s\}$))

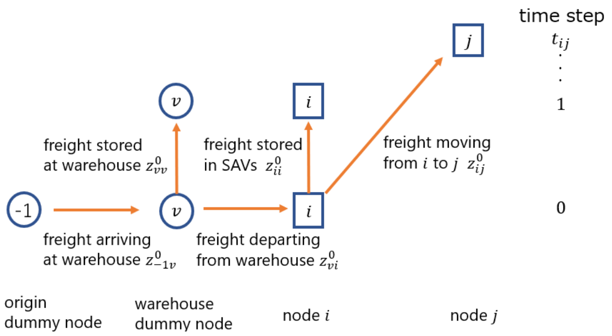


Fig. 2: Freight flow conservation at warehouse dummy node in time-expanded network

that of freight. Dummy nodes -1, 0, and 1 represent origin, freight receipt, and destination, respectively. The node conservation law of SAVs and passengers with no freight demand is identical to [15,19]. Fig. 2 shows freight flow at a warehouse dummy node. The waiting flow at the warehouse dummy node v describes storing the freight in the warehouse, whereas that at node i on the road network describes storing it in SAVs.

The flows of passengers, freight, and SAVs are constrained by traffic and vehicle capacities. Eq. (12) represents the vehicle capacity constraint. The third term on the left-hand side of Eq. (12) represents the volume of the served passengers themselves and their received freight. Eqs. (13)(14) are traffic capacity constraints on links and nodes, respectively. Eqs. (15)(16) describe inventory capacity constraints. Freight is stored in SAVs when it stays at a node on the road network rather than warehouses or SDLs, as shown in Eq. (15), otherwise, it can be stored at facilities, as shown in Eq. (16).

The integrated transportation system must satisfy passenger traffic and freight demand. Eqs. (17)(18) indicate departure and arrival constraints at origin and destination nodes, respectively, for passengers without freight demand. Eqs. (19)(20) describe departure con-

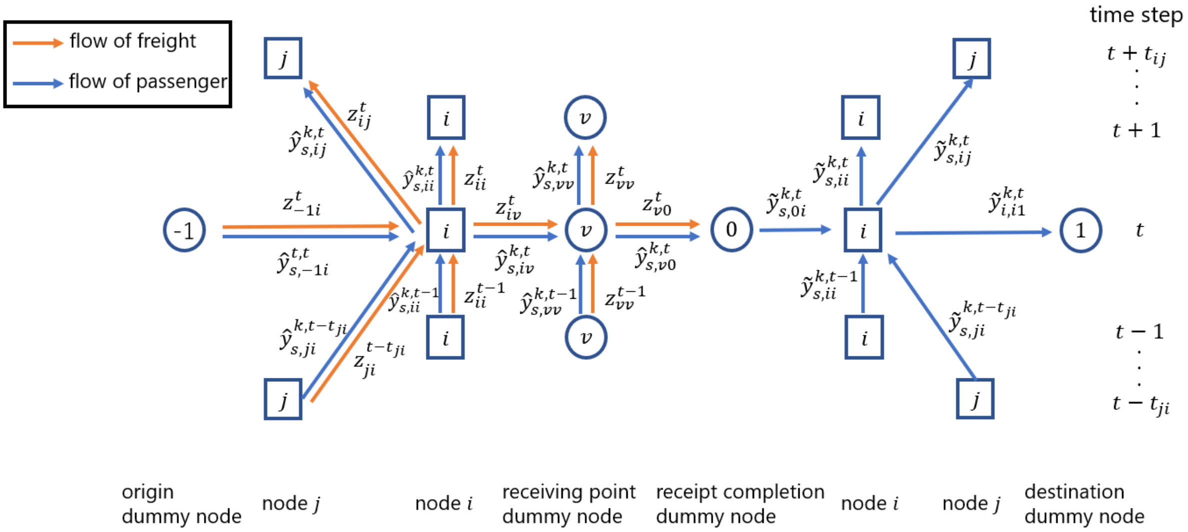


Fig. 3: Freight and passenger flow conservation in time-expanded network

straints for unserved and served passengers with freight demand, respectively, and Eq. (21) means arrival constraints for passengers with freight demand. Passengers with freight demand, departing from the origin, pick up their freight at SDLs and then travel to their destinations, or they move directly to their destinations and pick up their freight there, as shown in Eqs. (19)–(21). Eqs. (22)(23) explain departure and arrival constraints for freight. Eq. (22) ensures that all freight demand is satisfied, Eq. (23) represents the synchronization that freight service is completed only when freight and passengers are available to each other. Fig. 3 shows the flows of freight and passenger with freight demand from origin to destination. The flow from the origin dummy node -1 to the receipt completion dummy node 0 represents the pick-up of freight by passengers. The receipt is represented by freight and passenger moving simultaneously to dummy node 0. After receiving their freight, the passengers start traveling to their own destinations.

In separated transportation systems, counterpart to integrated transportation, SAVs are divided into $\tilde{x}^t_{ij}$ and $\hat{x}^t_{ij}$, which carry only passengers and freight, respectively. The optimal strategy for separated transportation is the solution to the optimization problem in which vehicle capacity constraint (12) is rewritten as

$$\sum_{s,k} y^{k,t}_{s,ij} + \sum_{s,k} \hat{y}^{k,t}_{s,ij} + \sum_{s,k} (\sigma+1)\tilde{y}^{k,t}_{s,ij} \leq \rho \tilde{x}^t_{ij} \qquad \forall ij \in \boldsymbol{E}, i \neq j, t, \quad (27)$$

$$\sigma z^t_{ij} \leq \rho \hat{x}^t_{ij} \qquad \forall ij \in \boldsymbol{E}, i \neq j, t. \quad (28)$$

2.3 Solution Method

Solving a multi-objective optimization problem involves deriving its Pareto frontier, which is a set of the Pareto efficient solutions [6]. In this study, the weighted-sum method—the standard solution method for multi-objective optimization [6]—draws a Pareto frontier of the proposed problem. The method iteratively solves the following single-objective optimization problem:

$$\min \alpha_T T + \alpha_D D + \alpha_N N + \alpha_C C + \alpha_S S \qquad (29)$$

subject to (2)–(26), where α is a non-negative constant that expresses the priority of each objective function.

The linearity of the proposed problem guarantees that the solutions of Eq. (29) with appropriate α are always all Pareto efficient solutions of Eq. (1). Therefore, the Pareto frontier can be approximated as a set of solutions of Eq. (29) with different α.

2.4 Qualitative Properties

This subsection describes the qualitative properties of the proposed model. Since the proposed problem is linear programming, according to the definition of the Pareto frontier—the lower envelope of a feasible domain, the larger feasible regions of the objective functions due to the relaxation of constraints ensure a weak Pareto improvement. Leveraging the mathematical property, it can be proved that an increase in vehicle capacity ρ, integration of freight and passenger flows, and installation of SDLs cause a monotonous non-increase in total travel time T, total travel distance D, total number of SAVs N, total infrastructure construction cost C, and total inventory S simultaneously. These mathematical properties can be expressed as follows:

Theorem 1 *For all ρ_1 and ρ_2 satisfying $\rho_2 > \rho_1 > 0$ and for all Pareto efficient solutions when $\rho = \rho_1$, there* *exist more weakly Pareto efficient solutions when* $\rho = \rho_2$.

Proof In the proposed problem, ρ appears only in Eq. (12). From Eq. (12) and non-negative constraints, the feasible regions of x_{ij}^t, $y_{s,ij}^{k,t}$, $\hat{y}_{s,ij}^{k,t}$, $\tilde{y}_{s,ij}^{k,t}$, and z_{ij}^t monotonically expand as ρ increases. Thus, the feasible regions of T, D, N, C, and S also expand monotonically with increasing ρ. □

Theorem 2 *For all* $\rho > 0$ *with the same value with respect to separated and integrated transportation systems and for all Pareto efficient solutions in the former, there exist more weakly efficient solutions in the latter.*

Proof The difference between integrated and separated transportation systems is the vehicle capacity constraint. The former is subject to Eq. (12), while the latter is subject to Eqs. (27)(28). From non-negative constraints, the feasible regions of x_{ij}^t, $y_{s,ij}^{k,t}$, $\hat{y}_{s,ij}^{k,t}$, $\tilde{y}_{s,ij}^{k,t}$, and z_{ij}^t under Eq. (12) are larger than those under Eqs. (27)(28) and $x_{ij}^t = \hat{x}_{ij}^t + \tilde{x}_{ij}^t$. Thus, employing integrated transportation instead of its counterpart enlarges the feasible regions of T, D, N, C, and S simultaneously. □

Theorem 3 *For all Pareto efficient solutions where the passengers can receive their freight either at SDLs or destination exclusively, there exist more weakly efficient solutions where they can receive it at both.*

Proof Since $\boldsymbol{\mathcal{V}}_s^{\mathrm{L}} \supseteq \boldsymbol{\mathcal{V}}^{\mathrm{L}}$ and $\boldsymbol{\mathcal{V}}_s^{\mathrm{L}} \supseteq \{s\}$, switching the locations where passengers can receive freight from only either destination $\{s\}$ or SDLs $\boldsymbol{\mathcal{V}}^{\mathrm{L}}$ to both $\boldsymbol{\mathcal{V}}_s^{\mathrm{L}}$ relaxes Eqs. (20)(23). Then, from non-negative constraints, feasible regions of $\hat{y}_{s,ij}^{k,t}$, $\tilde{y}_{s,ij}^{k,t}$, and z_{ij}^t are enlarged; thus, the feasible regions of T, D, N, C, and S also expand monotonically. □

2.5 Limitation of Model

The proposed problem for integrated transportation describes the routes of individual passengers, freight, and vehicles as continuous flows for unified decision-making on passenger, freight, and SAV routes, schedules, freight and passenger matching, and road, parking, and inventory capacity design. While it is less rigorous than models that treat each decision separately due to its macroscopic nature, this approximation ensures mathematical tractability, providing a useful benchmark for assessing operational performances for strategic designing. The limitations of the model are as follows:

– Routes of individual SAVs, passengers, and freight cannot be uniquely identified, since each SAV, passenger, and freight movement is represented by an aggregated flow.
– SAVs waiting on a node for parking or in congestion cannot be distinguished. Similarly, since we cannot completely identify whether an SAV is carrying passengers or freight, the SAV is simply stopping, transferring, or repacking cannot be distinguished.

3 Numerical Experiments

This section evaluates quantitatively the Pareto improvement by the employment of integrated transportation and SDLs. Section 3.1 describes the parameter settings in our experiments, and Section 3.2 shows the experimental results and discussion.

3.1 Numerical Settings

Our numerical experiments used traffic demand and network data extracted from the New York yellow taxi trip data. The generation procedure is the same as in Seo and Asakura [19]. The passenger demand data was extracted from the zone-based taxi travel records in Manhattan from 8:00 to 9:00 on April 1, 2019, for a total of 17,998 passengers. We input traffic records aggregated with a 5-minute time discretization width and a 30-minute departure time aggregation width as time-dependent passenger demand into the optimization problem.

The New York City network consisted of nodes representing each zone and links connecting neighboring zones. The free-flow travel time t_{ij} and the distance d_{ij} were assumed as 5 minutes and 1 km, respectively. The values of c_{ij} and c_i were determined to be proportional to the land value of each zone. We assume $\hat{c}_v$ to be equal to c_i at the corresponding node.

The other model parameters were set as follows: $\rho = 4$, $\sigma = 2$, $\gamma = 1$, $\mu^{\min} = 4$, $\mu^{\max} = 40$, $\kappa^{\min} = 4$, $\kappa^{\max} = 40$, and the maximum allowable travel time was 30 minutes. $\epsilon^{\min}$ and $\epsilon^{\max}$ were assumed to be 0 and sufficiently large, respectively, to represent the macroscopic facility location design. The maximum number of warehouses was 30, and that of SDLs was different in some cases. The locations of SDLs and warehouses are randomly selected on nodes in the network, and optimal facility location is left to future studies.

We approximated the Pareto frontier by iteratively calculating the optimization problem with various α. The weight parameter for T, α_T was varied between 0.1-10, while the others were fixed at $\alpha_D = 1$, $\alpha_N = 10$, $\alpha_C = 9$, $\alpha_S = 10$. We note that the values of α are not rigorously consistent with reality, but the objective of this study is to explore trade-off relations, not a single optimal solution with appropriate α.

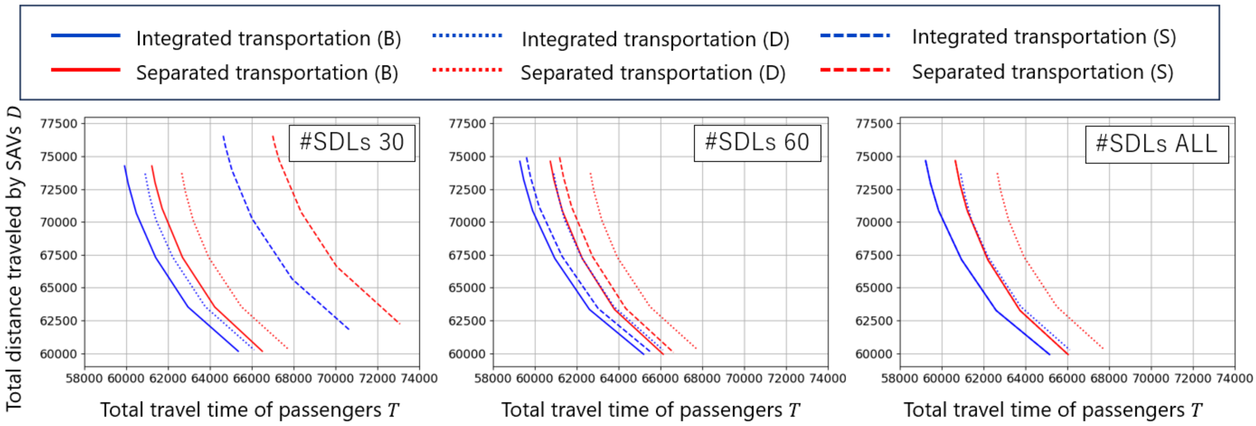


Fig. 4: Pareto frontiers (left: 30, center: 60, right: 67 for the number of SDLs)

Table 4: Percentage of passengers receiving freight at SDLs in the B-30 case

percentage of passengers with freight demand	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Integrated transportation	43.6%	40.0%	40.6%	45.4%	45.1%	49.4%	47.3%	50.4%	49.3%	47.9%
Separated transportation	32.6%	30.1%	34.3%	32.1%	32.6%	38.2%	36.9%	38.5%	39.5%	39.2%

Our numerical experiments considered the following cases. Three cases for the number of SDLs were set: 30, 60, and 67 (equal to the number of nodes in the network). Furthermore, we evaluated three cases for the location where passengers can receive their freight: destination only, SDL only, and both. The above cases are referred to as D-X, S-X, and B-X cases, respectively, where X denotes the number of SDLs.

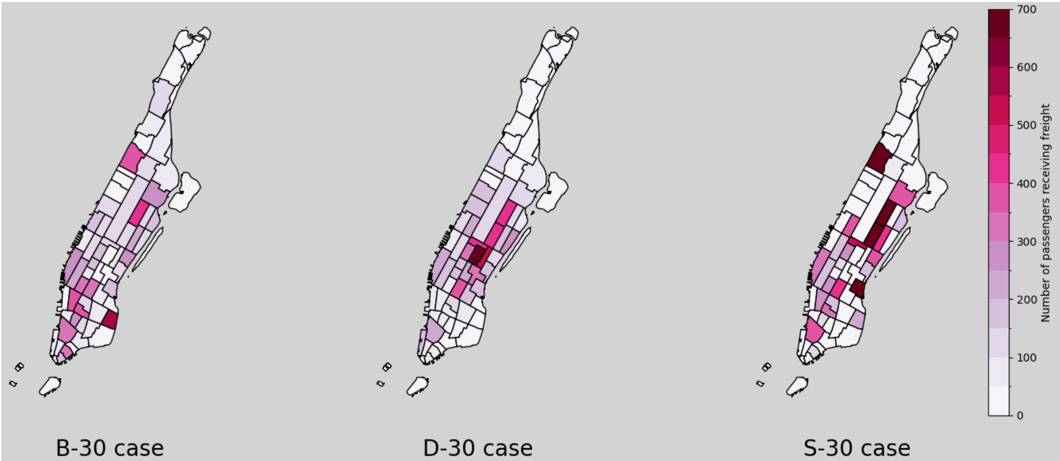
3.2 Results and Discussion

The Pareto frontier of each case is presented in Fig. 4 Although the actual Pareto frontier is five-dimensional, a two-dimensional relation (i.e., a cross-section of the actual Pareto frontier) is drawn to illustrate its important features. We note that other two-dimensional Pareto frontiers also have similar convex shapes. The horizontal and vertical axes depict the total travel time of passengers T and the total distance traveled by SAVs D, respectively. The left, center, and right of Fig. 4 compare the Pareto frontiers of integrated and separated transportation where the number of SDLs is 30, 60, and 67, respectively. The blue and red lines show the Pareto frontiers of integrated and separated transportation, respectively. The solid, dotted, and dashed lines show the Pareto frontiers in the B-case, D-case, and S-case, respectively.

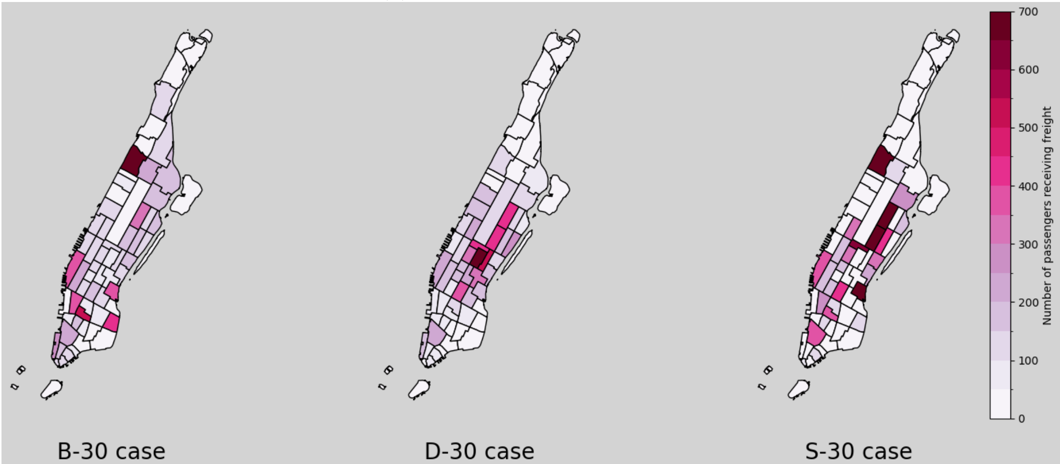
Comparing three figures in Fig. 4, we can explore the impact of the employment of SDLs on the Pareto improvements. The solutions in the S-case are significantly Pareto-improved with the number of SDLs and eventually are consistent with that in the B-case. Note that this does not mean that freight is received only at SDLs in the B-case; only the objective function is almost the same as that of the S-case. However, the solutions in the S-case are not Pareto efficient compared to those in the D-case unless SDLs are installed at most nodes. The solutions in the B-case are Pareto efficient compared to other cases, and the increase is slight as the number of SDLs increases. The results suggest that, regardless of the employment of integrated transportation, SDLs can provide Pareto improvements, although would not replace classical delivery to specific locations, such as homes or workplaces.

Table 4 compares the percentage of passengers receiving freight at SDLs in the B-30 case between integrated and separated transportation. From Table 4, we can confirm that the percentage of passengers receiving freight at SDLs in the integrated transportation system is higher than that in the separated transportation system, regardless of the passenger freight demand. The differences are caused by the mechanism of separated transportation, which fragments the freight and passenger flows at SDLs. These results indicate that integrated transportation is more likely to benefit from the employment of SDLs than its counterpart, suggesting that the integration with respect to urban space and vehicles synergistically provides the Pareto improvements.

Fig. 5 shows the spatial distribution of the number of passengers receiving freight in the case of 30 SDLs. Fig. 5(a) and (b) show the distribution in the integrated and separated transportation systems, respec-



(a) Integrated transportation



(b) Separated transportation

Fig. 5: Spatial distribution of the number of passengers receiving freight in the case of 30 SDLs

tively. The distribution in the B-30, D-30, and S-30 cases appears from left to right, respectively. Darker colors indicate a higher number of passengers receiving freight in the zone. Comparing the distribution in the B-30 case and other cases shows that the change in the spatial distribution between integrated and separated transportation is significant. These results suggest that the simultaneous employment of integrated transportation and SDLs for Pareto improvement requires a significantly different operational and infrastructure design compared to the conventional.

4 Conclusion

This study develops a multi-objective optimization model for integrated freight and passenger transportation. The proposed model describes the flows of passengers, freight, and SAVs using a DTA framework to capture the dynamic features of integrated transportation in SAV systems such as congestion propagation and ride-sharing matching of freight and passengers. This study formulates the proposed model as a multi-objective linear optimization problem; thus, we can easily calculate the Pareto frontier—a set of the Pareto efficient solutions. Decision-makers can select a suitable solution from the Pareto frontier based on their strategic policy. Furthermore, the linearity of the problem provides useful mathematical properties for system design: integrated transportation can simultaneously improve passenger convenience and social costs.

Numerical experiments validate the Pareto improvement by the employment of integrated transportation and SDLs. Furthermore, compared to separated transportation, integrated transportation is likely to benefit from SDLs, and requires a significantly different operational and infrastructure design.

Future studies could extend the model to a multimodal transportation system, where SAVs serve last-mile deliveries and fixed-route public transits cover long-haul transportation. The most critical strategy for multimodal transportation is the facility location of transport hubs synchronizing last-mile and long-haul transportation, as well as the scheduling of public transit. A dynamic programming approach can be adopted for this problem, where the first stage problem solves the network design including facility location, and the subsequent stages solve the dynamic routing and ride-sharing matching of SAVs, passengers, and freight.

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Conflict of Interest statement The authors declare that they have no conflict of interest.

CRediT authorship contribution statement
YI: Methodology, Software, Validation, Formal analysis, Writing - Original Draft, Visualization, **RK:** Conceptualization, Methodology, Formal analysis, Writing - Review & Editing, Supervision, **TS:** Methodology, Writing - Review & Editing, Supervision, Project administration.

Ethics approval and consent to participate
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Consent for publication Not applicable.

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List of Abbreviations

Abbreviations	Definition
SAV	shared autonomous vehicle
SDL	shared delivery location
DTA	dynamic traffic assignment

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