Group-and-Match vs. Route-then-Insert? Order Dispatching in Vehicle-Based Dual Services (VeDuS)

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Extended abstract submitted for presentation at the 12th Triennial Symposium on Transportation Analysis conference (TRISTAN XII)
June 22-27, 2025, Okinawa, Japan

March 2, 2025

Keywords: Vehicle-Based Dual Services, Passenger Mobility, Parcel Delivery, Order Dispatching

1 INTRODUCTION

Rapid urban transportation and delivery demand and relevant resource constraints have driven the need for more efficient vehicle utilization. An innovative concept, "Vehicle-based Multi-Services" (VeMuS), is a service model in which a single vehicle offers multiple services simultaneously in an urban mobility system. Similarly, "Vehicle-based Dual Services" (VeDuS) refers to a vehicle that provides two services simultaneously (Sun *et al.*, 2023).

This study considers the order dispatching problem for the most common dual services, in which a vehicle simultaneously provides parcel delivery and passenger mobility. The demand profile for parcel delivery orders is known in advance, whereas passenger transport orders dynamically arrive in real time. There are two primary strategies for dispatching these orders to vehicles. The first, the group-and-match (GM) strategy, is commonly used in on-demand ridesharing services. Passenger and parcel orders with similar itineraries are grouped and matched to vehicles. It leverages the bipartite structure between orders (both parcels and passengers) and vehicles and formulates order dispatching as an online matching problem (Lyu *et al.*, 2024). The second, the route-then-insert (RI) strategy, first generates initial routes for early-arriving orders (parcels) and then inserts dynamically arriving orders (passengers) during operations. Initial routes save computational cost in real-time large-scale decisions (Jaillet *et al.*, 2016).

Selection of a well-designed order-dispatching strategy can enhance service quality and resource utilization. However, this involves trade-offs between multiple objectives, complex constraints, service prioritization design, and expensive computational costs. Although many studies and practitioners adopt certain variants of either the GM or RI strategy in on-demand transportation, their performance and implications for VeDuS have not been compared. This study investigates order-dispatching strategies for VeDuS and explores how various factors influence their performance. Practical suggestions and valuable insights are provided.

2 PROBLEM STATEMENT

Without loss of generality, we make the following assumptions. (i) Demand: Parcel orders are known in advance, and passenger orders are dynamically requested in real time. Passenger orders typically yield higher revenue and have tighter time constraints compared with parcel orders. (ii) Simultaneous service: One passenger order and several parcel orders can share a vehicle with capacity constraints. Two passenger orders cannot share a vehicle space, and this assumption can be relaxed in a more general model.

We consider a fleet of vehicles $\mathcal{K}$ with capacity Q to serve two types of orders. Let $\bar{\mathcal{O}}_s$ be a set of parcel orders and $\tilde{\mathcal{O}}_d$ be a set of passenger orders. An order $o \in \bar{\mathcal{O}}_s \cup \tilde{\mathcal{O}}_d$ consists of a tuple $(l_o^a, l_o^b, u_o, \tau_o^a, \tau_o^b, \lambda_o, c_o, p_o)$, where l_o^a denotes pickup location, l_o^b dropoff location, u_o request time, τ_o^a latest pickup time, τ_o^b latest dropoff time, λ_o capacity occupancy, c_o revenue for serving the order, and p_o penalty for cancellation. For passenger orders, $u_o > 0$, τ_o^a reflects the maximum waiting time and τ_o^b reflects maximum detour restrictions. For parcel orders, $u_o = 0$, and the value of $\tau_o^a - u_o, \tau_o^b - u_o$ are longer than that of passenger orders. Passenger orders have higher revenues and penalties than those for parcel orders.

Two phases of decision-making are considered: a planning phase and an operational phase. For uniformity, we use a finite discrete decision epoch $\mathcal{T} = \{0, 1, 2, ..., t^{\text{end}}\}$, where $t = 0$ is the planning phase and $t \in \{1, 2, ..., t^{\text{end}}\}$ is the operational phase with a fixed time interval t_Δ. In each epoch $t \in \mathcal{T}$, a set of parcel orders $\bar{\mathcal{O}}_s(t = 0)$ and passenger orders $\{o \in \tilde{\mathcal{O}}_d : t - 1 < u_o \leq t\}(t \geq 1)$ are placed and added to unassigned orders set $\bar{\mathcal{S}}_t$ and $\tilde{\mathcal{S}}_t$, respectively. We need to dispatch order $o \in \bar{\mathcal{S}}_t \cup \tilde{\mathcal{S}}_t$ to a vehicle $k \in \mathcal{K}$ or postpone it to the next epoch $t + 1$. The set of unassigned orders become $\bar{\mathcal{S}}_t'$ and $\tilde{\mathcal{S}}_t'$ after dispatching. The reward in each epoch t is captured by a complex incremental revenue R_t^Δ as follows:

$$R_t^\Delta = \underbrace{\sum_{o \in (\bar{\mathcal{S}}_t \setminus \bar{\mathcal{S}}_t') \cup (\tilde{\mathcal{S}}_t \setminus \tilde{\mathcal{S}}_t')} c_o}_{(a)} - \underbrace{\sum_{o \in \bar{\mathcal{S}}_t' \cup \tilde{\mathcal{S}}_t' : \tau_o^a < t+1} p_o}_{(b)} - \alpha \underbrace{\sum_{o \in \tilde{\mathcal{S}}_t \setminus \tilde{\mathcal{S}}_t'} \left(\frac{(t_o^b - t_o^a)}{d_{l_o^a, l_o^b}/v} - 1\right)}_{(c)} - \beta \underbrace{\sum_{o \in \tilde{\mathcal{S}}_t \setminus \tilde{\mathcal{S}}_t'} (t_o^a - u_o)}_{(d)} - \underbrace{\sum_{k \in \mathcal{K}} D_k^\Delta}_{(e)}. \tag{1}$$

The system gains the reward from (a) revenue of served orders, minus (b) penalties for orders that exceed the latest pickup time, (c) penalties on passenger detour, (d) penalties on passenger waiting time, and (e) changes in travel distance costs for vehicles. The objective is to maximize the total reward $\sum_{t \in \mathcal{T}} R_t^\Delta$ in the entire time period.

While it is easy to use a binary variable x_{ok}^t to indicate whether an order o is dispatched to vehicle k in epoch t, the decision entails two challenges: (1) complex trade-offs between services for the two types of orders and (2) complex constraints in construction of the route—e.g., time and load constraints. For the GM and RI strategies:

• The group-and-match (GM) strategy makes dispatching decisions only in the operational phase $\forall t \in \{1, 2, ..., t^{\text{end}}\}$, in which parcel and passenger orders with similar itineraries are grouped and matched to vehicles. This approach reduces computational requirements by limiting the number of orders considered in each epoch.

• The route-then-insert (RI) strategy generates initial routes for parcel orders in $t = 0$ in the planning phase, then dynamically inserts passenger orders to routes in the operational phase $\forall t \in \{1, 2, ..., t^{\text{end}}\}$. This approach demands computational efforts for the initial routes in the planning phase, which offers computational efficiency for the operational phase.

3 SOLUTION APPROACH

3.1 Group-and-match strategy

Define an order group as a subset of unserved orders in $\bar{\mathcal{S}}_t$ and $\tilde{\mathcal{S}}_t$ at each epoch t. The set of all possible order groups is defined as $\mathcal{G} = \{(\bar{\mathcal{S}}_g, \tilde{\mathcal{S}}_g) | \sum_{o \in \bar{\mathcal{S}}_g \cup \tilde{\mathcal{S}}_g} \lambda_o \leq Q, |\tilde{\mathcal{S}}_g| \leq 1, \forall \bar{\mathcal{S}}_g \subseteq \bar{\mathcal{S}}_t, \forall \tilde{\mathcal{S}}_g \subseteq \tilde{\mathcal{S}}_t\}$. The maximum number of candidate order groups is $|\mathcal{G}| \sim O(|\tilde{\mathcal{S}}_t||\bar{\mathcal{S}}_t|^{\frac{Q}{\min_{o \in \bar{\mathcal{S}}_t} \lambda_o}})$. For an order group $g \in \mathcal{G}$ and a vehicle $k \in \mathcal{K}$, we denote $c_{gk} = \sum_{o\in\bar{\mathcal{S}}_g\cup\tilde{\mathcal{S}}_g} c_o - \alpha \sum_{o\in\bar{\mathcal{S}}_g}(\frac{(t_o^b - t_o^a)}{d_{l_o^a,l_o^b}/v} - 1) - \beta \sum_{o\in\tilde{\mathcal{S}}_g}(t_o^a - u_o) - D_{gk}^{\Delta}$ as the revenue of dispatching group g to vehicle k. The match between order groups and vehicles can be formulated as a linear integer programming as follows:

$$\max \sum_{k\in\mathcal{K}} \sum_{g\in\mathcal{G}} c_{gk} y_{gk} - \sum_{o\in\bar{\mathcal{S}}_t\cup\tilde{\mathcal{S}}_t:\tau_o^a<t+1} p_o \chi_o \tag{2}$$

s.t.

$$\sum_{k\in\mathcal{K}} \sum_{g\in\mathcal{G},o\in\bar{\mathcal{S}}_g\cup\tilde{\mathcal{S}}_g} y_{gk} + \chi_o = 1, \forall o \in \bar{\mathcal{S}}_t \cup \tilde{\mathcal{S}}_t \tag{3}$$

$$\sum_{k\in\mathcal{K}} y_{gk} \le 1, \forall g \in \mathcal{G} \tag{4}$$

$$\sum_{g\in\mathcal{G}} y_{gk} \le 1, \forall k \in \mathcal{K} \tag{5}$$

$$y_{gk} \in \{0,1\}, \forall g \in \mathcal{G}, \forall k \in \mathcal{K}, \tag{6}$$

$$\chi_o \in \{0,1\}, \forall o \in \bar{\mathcal{S}}_t \cup \tilde{\mathcal{S}}_t, \tag{7}$$

The objective function (2) maximizes total revenue while penalizing unserved orders. Constraints (3) ensure that each order is assigned to one group or postponed to the next epoch. Constraints (4) ensure that each group is assigned to at most one vehicle. Constraints (5) ensure that each vehicle is assigned to at most one order group. y_{gk} indicates whether order group g is assigned to vehicle k; χ_o indicates whether order o is postponed.

3.2 Route-then-insert strategy

In the RI strategy, in each epoch t, we can maximize incremental revenue R_t^{Δ} in Eq. (1) since it increases revenue and reduces penalties and costs. Let binary decision variable z_{ij}^k denote whether vehicle k moves from node i to node j. The insert and (re)routing problem at each epoch can be formulated as a dial-a-ride problem, which is often solved by heuristics due to large problem complexity and fast-computation requirement in the operational phase.

Both the initial routing and dynamic insertion can be solved via an adaptive large neighborhood search (ALNS) method. In the planning phase, ALNS can provide high-quality initial routes for parcel orders. In the operational phase, ALNS takes the initial routes as a warm start for the insertion decisions. Technically, ALNS can employ multiple destroy and repair operators, with each assigned a weight that is dynamically adjusted based on its performance during the iteration. We highlight the fact that ALNS can also remove unserved parcel orders from routes in the dynamic insertion process. Selection of the operator uses a roulette mechanism: Operators that performed well in previous iterations are more likely to be chosen in subsequent iterations. Newly generated solutions are accepted based on a simulated annealing mechanism. Once a maximum running time is reached, the ALNS stops and returns the routes.

4 NUMERICAL STUDY

The numerical study simulates a fleet of 10 vehicles operating within a 20 km × 20 km area in three hours with a 5-minute time interval. The pickup and drop-off points of an order are generated around different centers with 1 km standard deviation (see Figure 1). For scenarios with varying demand levels (Low: 20; Medium: 50; High: 100) and ratios of passenger orders (from 20 % to 80 % with an interval of 10 %), GM and RI strategies are implemented and evaluated in five instances per scenario. In Figure 2, the y-axis is the reward of the GM strategy $\mathbf{R}_{\mathrm{GM}}$ over the reward of the RI strategy $\mathbf{R}_{\mathrm{RI}}$. A value greater than 1 indicates better performance by the GM strategy. Results show similar performance of GM and RI under low demand levels, but significant differences under high demand levels: GM performs well at low passenger ratios, while RI excels at high passenger ratios. Figure 3 shows the performance of 3 specific instances based on 5 metrics: parcel service rate, passenger service rate, average travel distance for both parcels and passengers, average waiting time for passengers, and average detour for passengers. It shows that GM fulfills most parcel orders, while RI achieves a better passenger service rate, despite longer waiting times. We also conduct a sensitive analysis of the deviation of the spatial distribution but do not observe any clear patterns. The performance factors can be attributed to the computational complexity and how to anticipate passenger demand: RI offers more flexible insertion than GM, making it more efficient in scenarios with a high passenger ratio.

In the full version of the paper, we will include a literature review, details on the problem statement and two strategies, propositions under specific cases, numerical experiments on different factors (vehicle capacity, types of parcel, etc.), and discussions of performance.

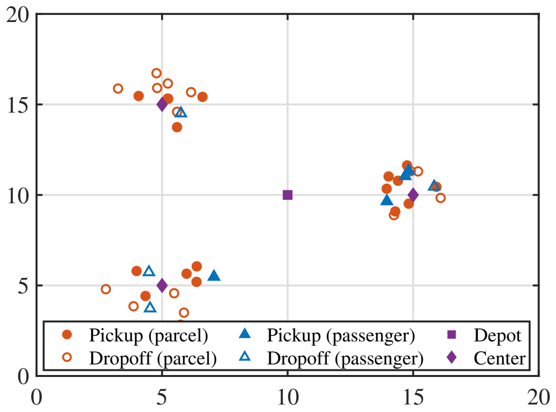

Figure 1 – *Service region*

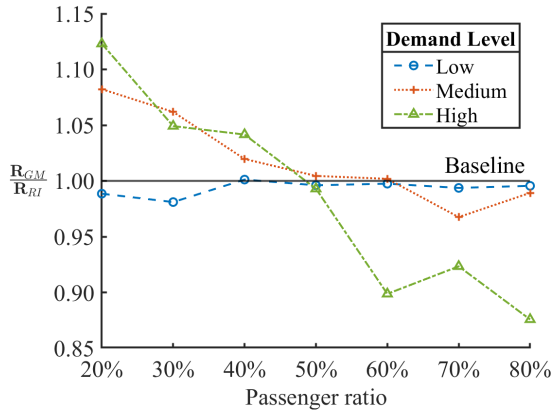

Figure 2 – *Impact of demand level and passenger ratio*

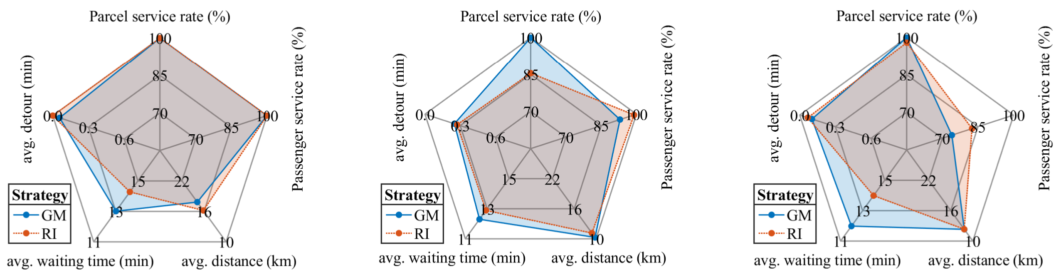

Figure 3 – *Performance in 3 instances: (a) Low demand level, passenger ratio 20%; (b) High demand level, passenger ratio 20%; (c) High demand level, passenger ratio 80%*

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