Modular Share-a-Ride Problem: An Approach for Combined Passenger and Freight Transport

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Short summary

This study introduces the modular share-a-ride problem (MSARP). In this problem, modular vehicles (MVs), individually dedicated to serving either passengers or parcels, can couple and decouple platoons at service nodes, thereby enabling combined passenger and freight transport. The objective is to determine the optimal routing, fleet allocation, and (de)coupling decisions to maximize total profit. The problem is firstly formulated as a mixed-integer linear programming (MILP) model. To solve medium- and large-scale instances efficiently, a Q-learning based adaptive large neighborhood search (QALNS) algorithm is then proposed, which incorporates Q-learning algorithm and novel operators. These optimization components jointly achieve high-quality platoons and solutions. Finally, through extensive numerical experiments, the efficiency of the proposed algorithm are validated. The economic advantage of combined passenger and freight transport is further demonstrated.
Keywords: Adaptive large neighborhood search; Combined passenger and freight transport; Modular vehicles; Share-a-ride problem; Shared mobility.

1 Introduction

In the context of rapid urbanization, shared mobility has garnered significant attention from both academia and industry as a sustainable solution to traffic congestion and resource constraints. Combined passenger and freight transport has emerged as a particularly promising paradigm. This operational mode aims to integrate passenger and logistics flows by fully utilizing the capacity of vehicles, resulting in reducing operational costs. However, its practical implementation still faces several challenges. A primary obstacle is the potential conflict between passenger comfort and the presence of freight (Cheng et al., 2023).
Advancements in vehicle technology, particularly the emergence of modular vehicles (MVs), offer a novel perspective to resolve this dilemma. MVs are autonomous units that possess the unique capability to physically couple into a platoon or decouple to operate independently while en-route (Dakic et al., 2021). Fig. 1 illustrates three MVs coupled together to form a platoon.[1] When these vehicles form a platoon and travel together, they benefit from lower travel costs (Chen and Li, 2021). Additionally, they are able to segregate passengers from freight. Sliding doors are installed at the interfaces between adjacent modules (Lin and Zhang, 2024). Beyond resolving the trade-off between efficiency and comfort, the MVs can adjust capacity dynamically allowing operators to adapt to spatiotemporal variations in demand.
Recent studies have increasingly explored the potential of MVs across various domains, such as public transit systems (Chen et al., 2019), urban logistics (Zhou et al., 2025), taxi operations (Fu and Chow, 2023), and combined passenger and freight transport (Hatzenbühler et al., 2023; Sun et al., 2025). However, existing research on applying MVs to combined passenger and freight transport has not fully leveraged the advantages of en-route coupling and decoupling, nor has it sufficiently addressed passenger satisfaction and safety concerns. Therefore, this paper introduces the modular share-a-ride problem (MSARP). A key feature of the problem is that a single vehicle unit is dedicated to a specific load type and cannot transport passengers and parcels simultaneously. Two or more vehicle units can form a platoon or separate from one at any service node. The primary contributions of this paper can be summarized as follows:

- The modular share-a-ride problem (MSARP) is defined and formally modeled through a mixed-integer linear programming (MILP) formulation.
- An efficient Q-learning based adaptive large neighborhood search (QALNS) algorithm for the MSARP is proposed.

[1]Image source: https://www.next-future-mobility.com

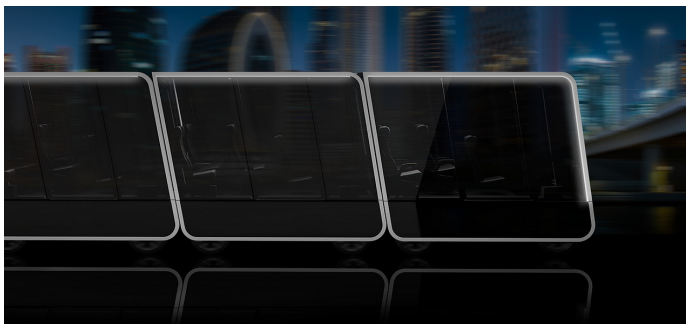


Figure 1: A platoon formed by three modular vehicles.

- Extensive computational experiments are conducted to demonstrate the effectiveness of the proposed QALNS algorithm and the economic benefits of using MVs.

2 Methodology

In this section, the MSARP is first formally defined, followed by the development of an MILP model for the problem. Finally, the proposed QALNS is briefly introduced.

Problem description

In the MSARP, an operator manages a homogeneous fleet of autonomous MVs that provide passenger and freight services in an urban environment. All requests are pre-booked, and their origins, destinations, time windows and loads, are known in advance. Each MV is restricted to carrying either passengers or parcels. At any node, two or more MVs can couple to form a platoon. This platooning creates a combined service capability: a platoon composed of at least one passenger-dedicated MV and one parcel-dedicated MV can serve both passenger and freight requests concurrently. Moreover, platoons can be decouple at any node. Fig. 2 illustrates an example of the MSARP. There are four MVs in total, including three passenger-dedicated MVs and one parcel-dedicated MV. MV 1 and MV 4 couple at the drop-off node of request 7 and travel as a platoon. They subsequently couple with MV 2 at the pickup node of request 4, forming a platoon consisting of three MVs. At the drop-off node of request 8, MV 4 decouples from the platoon and continues traveling independently. At the drop-off node of request 4, MV 1 and MV 2 decouple, while MV 2 and MV 3 couple to form a new platoon. Finally, MV 2 and MV 3 decouple at the drop-off node of request 6.
The objective is to determine vehicle routes, fleet allocation (i.e., each MV is designated to serve either passengers or parcels), and en-route coupling and decoupling operations of MVs so as to serve as many requests as possible and thereby maximize the operator's profit.

Problem formulation

The mathematical notations are summarized in Table 1. The objective function and the main constraints of the MSARP are presented as follows.
The Objective (1) represents the profit obtained by subtracting the travel costs from the revenue generated by serving requests.

$$\text{Max} \sum_{r\in\mathcal{P}^o}\left(\lambda+\gamma^A d_{o_r,d_r}\right)h_r+\sum_{r\in\mathcal{F}^o}\left(\mu+\gamma^B d_{o_r,d_r}\right)h_r-\gamma^C\sum_{k\in\mathcal{K}}\sum_{(i,j)\in\mathcal{A}}d_{ij}\left(x_{ijk}-\eta N_{ijk}\right). \tag{1}$$

Constraints (2) and (3) ensure that each MV serves either passengers or parcels, but not both. Constraints (2) and (3), which differ from those commonly found in the existing literature on flexible routing with MVs, can be regarded as newly proposed constraints to the problem setting considered in this study.

$$y_{ijkr}\le 1-z_k, \forall\,(i,j)\in\mathcal{A}, \forall k\in\mathcal{K}, \forall r\in\mathcal{P}^o, \tag{2}$$

$$y_{ijkr}\le z_k, \forall\,(i,j)\in\mathcal{A}, \forall k\in\mathcal{K}, \forall r\in\mathcal{F}^o. \tag{3}$$

Constraints (4) and (5) ensure that the onboard load of each MV, or each platoon, does not exceed its maximum capacity. They account for the capacity advantages that arise when two or more MVs form a

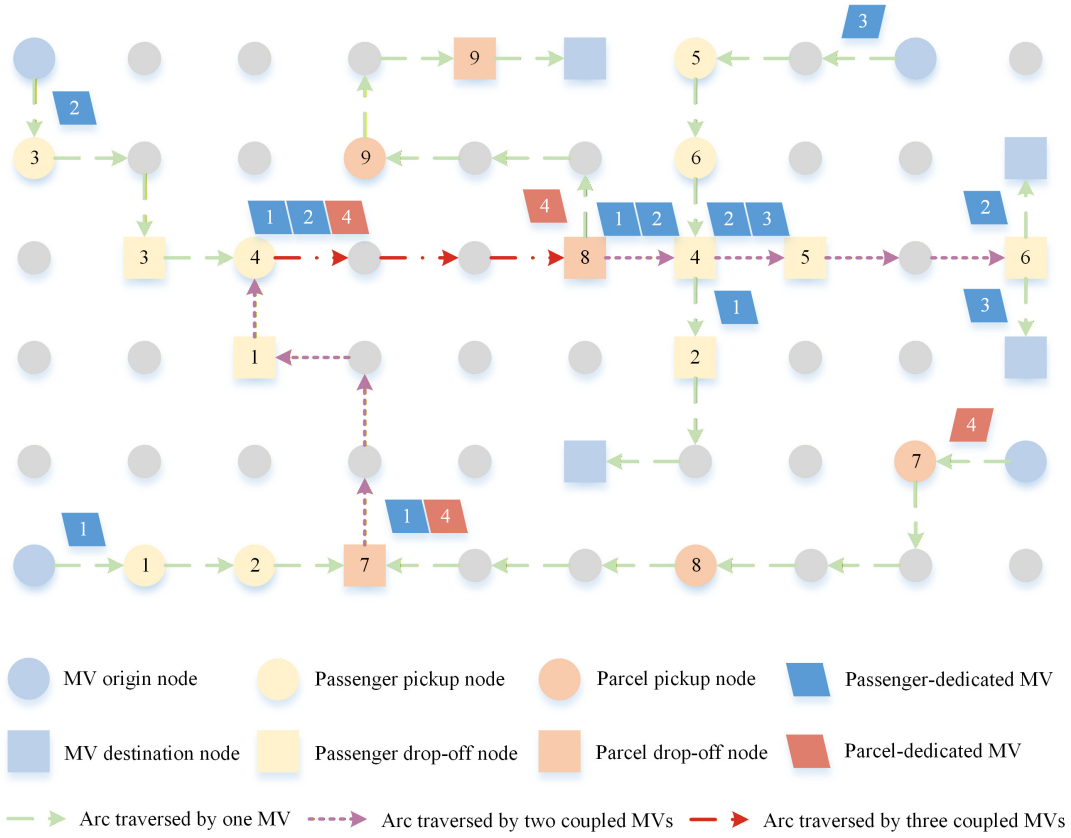


Figure 2: An example of the MSARP.

platoon. Particularly, we assume two MVs form a platoon whenever they traverse the same arc.

$$\sum_{k\in\mathcal{K}}\sum_{r\in\mathcal{P}^o} q_r y_{ijkr} \le \sum_{k\in\mathcal{K}} Q_k x_{ijk}\,(1-z_k), \forall\,(i,j)\in\mathcal{A}, \tag{4}$$

$$\sum_{k\in\mathcal{K}}\sum_{r\in\mathcal{F}^o} q_r y_{ijkr} \le \sum_{k\in\mathcal{K}} Q_k x_{ijk} z_k, \forall\,(i,j)\in\mathcal{A}. \tag{5}$$

Constraints (4) and (5) are nonlinear. Therefore, a auxiliary variable $u_{ijk} = x_{ijk}z_k$ is introduced to linearize them, resulting in linear Constraints (6)–(10).

$$\sum_{k\in\mathcal{K}}\sum_{r\in\mathcal{P}^o} q_r y_{ijkr} \le \sum_{k\in\mathcal{K}} Q_k\left(x_{ijk}-u_{ijk}\right), \forall\,(i,j)\in\mathcal{A}, \tag{6}$$

$$\sum_{k\in\mathcal{K}}\sum_{r\in\mathcal{F}^o} q_r y_{ijkr} \le \sum_{k\in\mathcal{K}} Q_k u_{ijk}, \forall\,(i,j)\in\mathcal{A}, \tag{7}$$

$$u_{ijk} \ge x_{ijk} + z_k - 1, \forall\,(i,j)\in\mathcal{A}, \forall k\in\mathcal{K}, \tag{8}$$

$$u_{ijk} \le x_{ijk}, \forall\,(i,j)\in\mathcal{A}, \forall k\in\mathcal{K}, \tag{9}$$

$$u_{ijk} \le z_k, \forall\,(i,j)\in\mathcal{A}, \forall k\in\mathcal{K}. \tag{10}$$

Constraints (11)–(15) are platooning constraints. Constraints (11) and (12) ensure that MVs traveling in the same platoon arrive at the next node simultaneously. Constraints (13) and (14) enforce that MVs traversing the same arc form a platoon. We set $k > v$, which reduces the number of variables P_{ijkv} by half compared with the case of $k \ne v$.

$$\alpha_{jk} - \alpha_{jv} \le M\left(1-P_{ijkv}\right), \forall\,(i,j)\in\mathcal{A}, \forall k\in\mathcal{K}, \forall v\in\mathcal{K}, k>v, \tag{11}$$

$$\alpha_{jv} - \alpha_{jk} \le M\left(1-P_{ijkv}\right), \forall\,(i,j)\in\mathcal{A}, \forall k\in\mathcal{K}, \forall v\in\mathcal{K}, k>v, \tag{12}$$

$$P_{ijkv} \ge x_{ijk} + x_{ijv} - 1, \forall\,(i,j)\in\mathcal{A}, \forall k\in\mathcal{K}, \forall v\in\mathcal{K}, k>v, \tag{13}$$

$$2P_{ijkv} \le x_{ijk} + x_{ijv}, \forall\,(i,j)\in\mathcal{A}, \forall k\in\mathcal{K}, \forall v\in\mathcal{K}, k>v, \tag{14}$$

$$N_{ijk} \le \sum_{v\in\mathcal{K},v<k} P_{ijkv} + \sum_{v\in\mathcal{K},v>k} P_{ijvk}, \forall\,(i,j)\in\mathcal{A}, \forall k\in\mathcal{K}. \tag{15}$$

In addition to the above primary constraints, the model also includes vehicle flow constraints, request flow constraints, time continuity constraints, time window constraints, and domains of the variables.

Table 1: Summary of the mathematical notations.

Type	Notation	Definition
Sets	$\mathcal{V}$	Set of nodes
	$\mathcal{A}$	Set of arcs
	$\mathcal{P}$	Set of pickup and drop-off nodes for passenger requests
	$\mathcal{P}^o$	Set of pickup nodes for passenger requests
	$\mathcal{P}^d$	Set of drop-off nodes for passenger requests
	$\mathcal{F}$	Set of pickup and drop-off nodes for freight requests
	$\mathcal{F}^o$	Set of pickup nodes for freight requests
	$\mathcal{F}^d$	Set of drop-off nodes for freight requests
	$\mathcal{R}$	Set of requests
	$\mathcal{K}$	Set of MVs
	$\mathcal{S}$	Set of origin nodes of MVs
	$\mathcal{E}$	Set of destination nodes for MVs
Parameters	o_r	Pickup node for request $r \in \mathcal{R}$
	d_r	Drop-off node for request $r \in \mathcal{R}$
	q_r	Demand of request $r \in \mathcal{R}$
	s_k	Origin node of MV $k \in \mathcal{K}$
	e_k	Destination node of MV $k \in \mathcal{K}$
	Q_k	Maximum capacity of MV $k \in \mathcal{K}$
	L	Maximum size of an MV platoon
	η	Platoon cost saving rate
	a_i	Start time at node $i \in \mathcal{V}$
	b_i	End time at node $i \in \mathcal{V}$
	d_{ij}	Travel distance of arc $(i, j) \in \mathcal{A}$
	t_{ij}	Travel time of arc $(i, j) \in \mathcal{A}$
	γ^A	Profit per kilometer for serving a passenger request
	γ^B	Profit per kilometer for serving a freight request
	γ^C	Average cost per kilometer for serving a request
	λ	Fixed profit obtained from serving a passenger
	μ	Fixed profit obtained from serving a parcel
Variables	α_{ik}	Arrival time of MV $k \in \mathcal{K}$ at node $i \in \mathcal{V}$
	β_{ir}	Arrival time of request $r \in \mathcal{R}$ at a node $i \in \{o_r, d_r\}$
	x_{ijk}	1 if MV $k \in \mathcal{K}$ traverses arc $(i, j) \in \mathcal{A}$, 0 otherwise
	y_{ijkr}	1 if MV $k \in \mathcal{K}$ carries request $r \in \mathcal{R}$ while traversing arc $(i, j) \in \mathcal{A}$, 0 otherwise
	z_k	1 if MV $k \in \mathcal{K}$ is carrying parcels, 0 otherwise
	h_r	1 if request $r \in \mathcal{R}$ is serviced, 0 otherwise
	P_{ijkv}	1 if MV $k \in \mathcal{K}$ and MV $v \in \mathcal{K}$ form a platoon while traversing arc $(i, j) \in \mathcal{A}$, 0 otherwise
	N_{ijk}	The number of vehicles platooning with MV $k \in \mathcal{K}$ on arc $(i, j) \in \mathcal{A}$
	u_{ijk}	1 if MV $k \in \mathcal{K}$ is carrying parcels while traversing arc $(i, j) \in \mathcal{A}$, 0 otherwise

Solution approach

The pseudocode of the algorithm is provided in Algorithm 1. In each iteration, an action is selected based on the Q-table, determining the removal number q. The removal operator generates a partial solution s_{rem}. The insertion operator then constructs a complete solution s_{ins}. Finally, the local search utilizes a novel platoon search operator, focusing on identifying opportunities for platoon formation, yielding a new improved solution s_{new}. This s_{new} is then accepted based on a simulated annealing criterion. The s_{new} and the number of non-improving iterations Ω are also used to update the current state, the reward, and the Q-table. Finally, when the number of iterations $Iter$ reaches the maximum number of iterations $Iter_{\max}$, the algorithm terminates.

3 Results and discussion

To ensure test cases are based on well-studied and realistic problems, the instances were adapted from three benchmark instance sets. The adapted instances are labeled as “mk-n", where $m \in \{a, b, u\}$ denotes the instance category, k represents the number of available vehicles, and n indicates the number of requests. The set of small-scale instances are solved using both CPLEX and the proposed QALNS algorithm. The

Algorithm 1 Q-learning based adaptive large neighborhood search

Input: Parameter configuration, Initial Q-table, the maximum number of iterations $Iter_{\max}$.
Output: The global best solution s_{best}.

Generate an initial solution s_{init} using a construction heuristic.
Initialize weights ω_d and ω_r for all removal and insertion operators.
$s_{cur} \leftarrow s_{init}, s_{best} \leftarrow s_{init}, Iter \leftarrow 0, \Omega \leftarrow 0$.
while $Iter < Iter_{\max}$ **do**
    Determine removal number q based on Q-table.
    Select a removal operator θ_d and a insertion operator θ_r based on their current weights ω_d, ω_r.
    $s_{rem} \leftarrow$ **Removal**(s_{cur})
    $s_{ins} \leftarrow$ **Insertion**(s_{rem})
    $s_{new} \leftarrow$ **LocalSearch**(s_{ins})
    if $f(s_{new}) \geq f(s_{cur})$ **then**
        $s_{cur} \leftarrow s_{new}, \Omega \leftarrow \Omega + 1$.
        if s_{new} is feassible $\wedge$ $f(s_{new}) > f(s_{best})$ **then**
            $s_{best} \leftarrow s_{new}, \Omega \leftarrow 0$.
        end if
    else
        if accept(s_{new}, s_{cur}) **then**
            $s_{cur} \leftarrow s_{new}$.
        end if
        $\Omega \leftarrow \Omega + 1$.
    end if
    Update the current state, reward and Q-table.
    $Iter \leftarrow Iter + 1$.
    Periodically update the operator weights ω_d, ω_r.
end while

results are detailed in Table 2. The average computational time for CPLEX is 2580.04 seconds. The proposed QALNS produces better lower bounds for 1 instance and the average computational time of the QALNS is only 0.03 seconds. Finally, the average value of Δ (the relative difference between the best objective value obtained by QALNS and CPLEX) is 0.10%.

The QALNS and the standard ALNS are applied to solve medium- and large-scale instances. Fig. 3 presents violin plots of the Δ_1 (the gap between the average and best objective values) distributions obtained by QALNS and ALNS across different instance types and problem scales, together with the average gap between their best objective values (i.e., average Δ_2). On large-scale instances, the QALNS demonstrates superior stability, characterized by smaller medians and lower dispersion of the Δ_1 distributions. Moreover, the line chart of the average Δ_2 indicates that the QALNS achieves better best objective values than ALNS. Finally, the economic advantage of combined passenger and freight transport is investigated. The corresponding results are reported in Table 3. The results show that combining transport can achieve higher profits, and the average gap between the best objective values obtained under combined transport and separate transport is 0.89%. This implies that enterprises should actively adopt MVs for combined passenger freight transport, as it offers economic advantages while maximizing customer satisfaction.

4 Conclusions

This study focus on the application of MVs for combined passenger and freight transport, introducing the modular share-a-ride problem (MSARP). In this problem, a fleet of MVs, dedicated to either passenger or parcel transport, can dynamically couple and decouple platoons en-route. A mixed-integer linear programming (MILP) model and a Q-learning based adaptive large neighborhood search (QALNS) algorithm are developed for the problem. Extensive computational experiments are conducted. On small-scale instances, the QALNS algorithm matches the optimal solutions found by CPLEX but in a fraction of the computational time. The algorithm also proves its scalability and robustness when applies to larger instances. In addition, combined passenger and freight transport can lead to profit improvements of 0.89%.

This study opens several promising avenues for future research. First, future work could consider transfer operations and electric MVs subject to charging constraints. Second, the current deterministic model could be extended to incorporate dynamic and stochastic elements. Another promising direction is the development of efficient exact approaches for the MSARP, which would contribute to a deeper theoretical understanding.

Table 2: Results for small-scale instances.

	CPLEX				QALNS			
Instance	*LB*	*UB*	*Gap*	$t(s)$	*Best*	*Avg.*	$t(s)$	Δ
a2-4	43.17	43.17	0.00	1.17	43.17	43.17	0.02	0.00
a2-5	66.51	66.51	0.00	70.63	66.51	65.49	0.05	0.00
a2-6	43.94	43.94	0.00	1205.67	43.94	43.94	0.03	0.00
a2-7	70.28	81.76	16.33	7200.00	**71.30**	71.30	0.09	1.45
a2-8	75.69	92.18	21.79	7200.00	75.69	75.69	0.06	0.00
b2-4	37.80	37.80	0.00	3.67	37.80	37.80	0.01	0.00
b2-5	90.15	94.25	4.55	7200.00	90.15	90.15	0.01	0.00
b2-6	46.72	46.72	0.00	68.28	46.72	46.72	0.02	0.00
b2-7	63.13	69.95	10.80	7200.00	63.13	63.03	0.03	0.00
b2-8	73.05	78.03	6.82	7200.00	73.05	73.05	0.04	0.00
u2-4	15.50	15.50	0.00	25.31	15.50	15.50	0.01	0.00
u2-5	23.69	23.69	0.00	5.65	23.69	23.69	0.01	0.00
u2-6	19.09	19.09	0.00	332.15	19.09	19.09	0.01	0.00
u2-7	31.98	31.98	0.00	3.92	31.98	31.98	0.02	0.00
u2-8	27.46	27.46	0.00	984.19	27.46	27.46	0.04	0.00
Average	48.54	51.47	4.02	2580.04	**48.61**	48.54	**0.03**	**0.10**

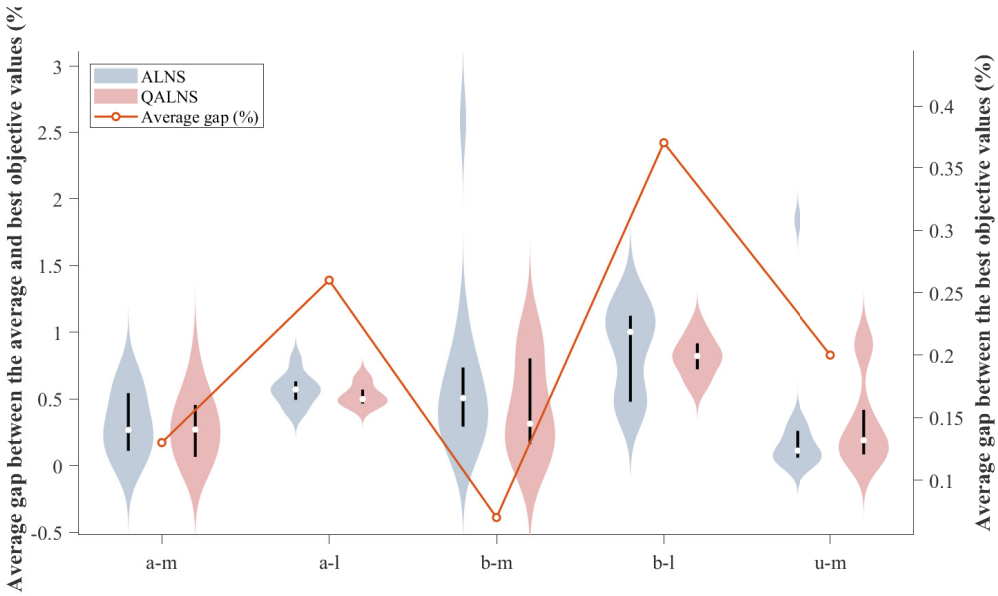


Figure 3: Stability comparison of QALNS and ALNS and the average gap in best objective values.

Table 3: Comparison between separate transport and combined transport

Separate transport			Combined transport			
Best	*Avg.*	$t(s)$	*Best*	*Avg.*	$t(s)$	Δ_2
643.66	640.73	43.06	**649.39**	645.94	92.88	**0.89**

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