Assessing the Resilience of Rebalancing Strategies for Ride-hailing Services in Multi-modal Transportation System

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INTRODUCTION

Resilience of a multi-modal transportation system is defined as a system's ability to resist and absorb the negative impacts of disruptions, maintain a certain service level, and recover promptly (Ju et al., 2017). Ride-hailing (RH) services, as on-demand mobility solutions, provide a promising way to enhance network resilience, as they can adapt to major disruptions. When integrated with public transportation, they provide seamless first- and last-mile options for multi-modal trips (Sunitiyoso et al., 2022).

Rebalancing strategy is one of the most important components of RH service operations. The strategies are based on either centralized or decentralized approaches. A centralized system maximizes overall performance, while a decentralized one maximizes the utility of each local system operator. However, selecting the appropriate strategy is not a simple task, especially in large service areas when considering transfers between multiple transportation modes. Disruption scenarios present further challenges, as most RH strategies have been tested under nominal scenarios with regular demand patterns. Therefore, it is crucial to investigate how RH services contribute to multi-modal transportation systems during disruptions, while also considering the impacts of demand predictability.

This study develops rebalancing strategies for RH mobility services in multi-modal transportation systems, as an extension of the work Lee & Leclercq (2025). A traffic simulation is established using a 900 km^2 urban toy network with multiple transportation modes, allowing users to transfer between different modes during their trips. The resilience of the system is compared across different rebalancing strategies in response to supply disruptions on train lines.

METHODOLOGY

1.1 Multi-modal Transportation System Representation

Road Network: A road network with a large service area is designed as the basic structure, as shown in Figure 1. The transportation modes include metros, trains, buses, RH vehicles and other vehicles. These modes are connected across different network layers by nodes, enabling users to transfer between them for multi-modal trips. All vehicles on the network are assigned the same speed at a given time step if they are in the same region and operate the same mode, following the multi-modal macroscopic fundamental diagram (MFD) principle (Mariotte et al., 2017). Since metros and trains are unaffected by traffic conditions, their average speeds are set at 13 m/s and 30 m/s, respectively.

Meanwhile, the speeds of buses and RH vehicles are determined by traffic conditions. Their speeds vary, with the maximum value of 15.5 m/s, depending on the number of vehicles accumulated in the regions. The speed formula for these vehicles is defined as follows:

$$v_m^r(t) = V_m^r\left(n_{m'}^r(t)\right), \quad \forall m' \in \mathcal{M} \tag{1}$$

Where, $v_m^r(t)$ represents the speed of vehicle type m in region r at time t. $\mathcal{M}$ represents all vehicle types considered in the simulation. The speed is determined by the speed-MFD function for vehicle type m, $V_m^r(\cdot)$, which uses different parameter values for each mode and captures the congestion dynamics and interactions between modes in region r at time t. $n_{m'}^r(t)$ denotes the number of vehicle type $m' \in \mathcal{M}$ in region r at time t. See Mariotte et al. (2017) for further details.

User Origin-Destination (OD) Distribution: The road network includes an urban area in the inner zone, an intermediate area, and a suburban area in the outer zone. The user OD distribution reflects evening commute patterns, with most users traveling from urban to suburban areas.

User OD pairs are determined by considering both spatial and temporal distributions. Urban areas have a high probability as origins and a low probability as destinations, while suburban areas have the opposite pattern. The temporal distribution defines users' departure times. The time gap between consecutive departures, in seconds per user, follows a normal distribution. However, arrival times depend on the transportation modes chosen and the prevailing traffic conditions.

User Trips: With the road network and the user OD distribution established, a two-step process is proposed for modeling user trips. In the first step, the Dijkstra method is employed as the pathfinding algorithm in the multi-modal network. The cost function is defined by the total travel time from origin to destination. Considering potential service delays due to transit frequency, capacity, and transfers, each user is assumed to find five candidate shortest paths. These paths may involve combinations of transportation modes. In the second step, a logit model is used to select a user path based on a utility function. The mathematical expression of the logit model is as follows:

$$U_i = V_i + \varepsilon_i = \sum_{q_i} \frac{d_t(q_i)}{v_t} + \sum_{p_i} \frac{d_m(p_i)}{v_m} + \sum_{l_i} \frac{d_b(l_i)}{v_b(l_i)} + \sum_{s_i} \frac{d_r(s_i)}{v_r(s_i)} + \varepsilon_i \tag{2}$$

$$P_i = \frac{e^{-\theta \times U_i}}{\sum_i e^{-\theta \times U_i}} \tag{3}$$

Where Equation 2 represents the random utility of path i, U_i, consisting of the deterministic component V_i and the unobservable error ε_i. The deterministic component V_i is calculated as the total sum of travel times for each transportation mode. Travel time for each mode is determined by dividing the trip lengths by the travel speeds. For regions q, p, l, and s in path i, $d_t(q_i)$, $d_m(p_i)$, $d_b(l_i)$, and $d_r(s_i)$ are trip lengths, and v_t, v_m, $v_b(l_i)$, and $v_r(s_i)$ are travel speeds of trains, metros, buses, and RH vehicles, respectively. Equation 3 represents the probability of a user choosing path i, P_i. Based on these probabilities, users select their paths and start their multi-modal trips.

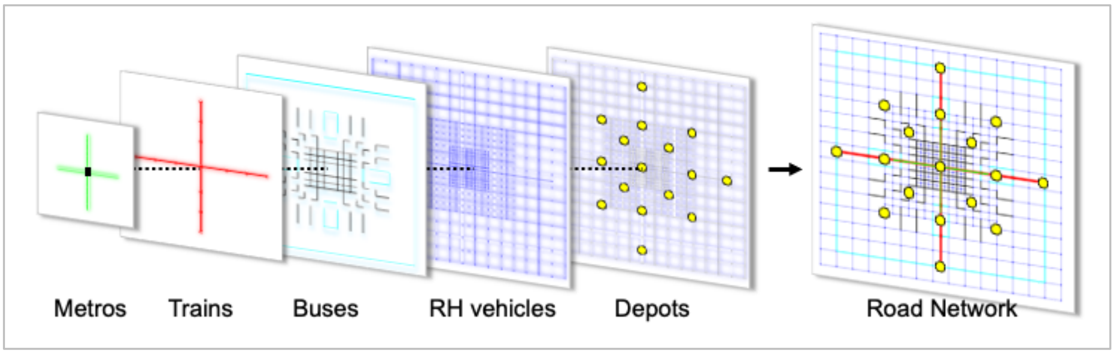

Figure 1 – *Multi-modal road network with different transportation layers*

1.2 RH Service Operations

Demand Prediction: It is assumed that RH system operators know the time and location of each user's origin. However, it remains uncertain which users will opt for RH vehicles. Based on the RH market share, operators expect that 10% of users in the next five minutes will request RH vehicles. To meet this expected demand, they provide drivers with designated depots for relocation. These depots are facilities where RH vehicles depart for service, and return afterward.
Operator and Driver Utilities: The RH system operator aims to ensure a sufficient number of vehicles are available to meet the expected demand. Therefore, the operator's utility for a service region is defined by the number of vehicles to be rebalanced. On the other hand, the driver's utility is the expected revenue from serving passengers. Drivers of vacant vehicles receive relocation offers from operators to move to depots. Drivers accept or refuse these offers based on their utility function.

1.3 Rebalancing Optimization Approaches

With multi-modal transportation systems and RH service operations, three different optimization approaches are developed for the operators and drivers: centralized, decentralized, and multi-agent reinforcement learning (MARL). Each approach proposes a methodology for rebalancing RH vehicles to depots, addressing local supply-demand imbalances during disruptions.

Centralized Approach: This approach assumes that a single system operator manages RH services for the entire network. The main objective is to maximize the total sum of operator and driver utilities. Rebalancing is performed by identifying the optimal matching of vacant vehicles to depots that yields the highest system utility (Duan et al., 2020).

Decentralized Approach: In this approach, the network is managed by multiple local operators, each covering a separate service region. Operators negotiate with drivers to maximize their own utilities. It is unlikely that any individual operator or driver will follow matching assignments based on overall system costs. They are primarily motivated by their self-interest and aim to maximize individual utilities. An auction-based Gale-Shapley matching method is developed to optimize the rebalancing process (Seppecher & Leclercq, 2023).

MARL Approach: This approach designates vacant vehicles as *Agents*. Their objectives are to minimize average vacant time. To achieve this, their *Actions* are selecting optimal depots for relocation. For *States*, both global and local observations are considered. The global observation includes (i) expected incomes if relocating to depots, (ii) the number of vehicles already relocated to depots, (iii) the number of alternative transportation modes available around depots, and (iv) local supply-demand imbalances at each depot. The local observation includes the number of vacant vehicles near each agent, allowing agents in similar situations to cooperate with each other (Lowe et al., 2017). *Reward* is defined based on the time it takes for a vacant vehicle to be matched with a passenger. A higher positive reward is given if the vehicle is matched more quickly within a given time threshold. Conversely, a lower negative reward is applied as the vacant time extends beyond the threshold. The reward for agent i, R_i, is shaped as an exponential function as follows:

$$R_i = 20 \times \left(-\left(2 \times \frac{1}{1+e^{0.3\times(t_i-t_h)}} - 1\right)\right) \tag{4}$$

Where, t_i is the duration of time that agent i remains vacant, and t_h is the time threshold.

An actor-critic method is applied using a multi-agent deep deterministic policy gradient algorithm. The actor and critic networks are assumed to be identical for all agents. As a result, a method of centralized training and decentralized execution is implemented so that agents share the same training data while acting independently based on their own local observations.

PRELIMINARY RESULTS

The proposed rebalancing strategies are evaluated using a 900 km^2 grid Manhattan toy network. The network consists of 874 road segments of 500 m, 1 km, and 2 km links, and 576 intersections. The simulation runs for 3 hours with 4,357 trip users. Frequencies for trains, metros, and buses are set at 20 minutes, 6 minutes, and 10 minutes, respectively. The fleet size of RH vehicles is set at 400. Seventeen RH depots are strategically placed across the network for efficient rebalancing. A disruption on train lines lasts for one hour, occurring from 0.5 h to 1.5 h during the simulation.

The results of vehicle activities in Figure 2(a) show that, regardless of the approach, the number of serving vehicles increased rapidly during the disruption and gradually decreased afterward. Passenger waiting times in Figure 2(b) indicate that the MARL approach had the lowest values during both regular and disruption scenarios. In Figure 2(c), during the disruption, the baseline with no rebalancing strategy showed the steepest performance decline. The centralized and the decentralized approaches reached their lowest points at times but at the same level. The MARL approach showed an intermediate performance decline, with the smallest overall decrease. Therefore, it can be concluded that the MARL approach is the most resilient system against disruptions.

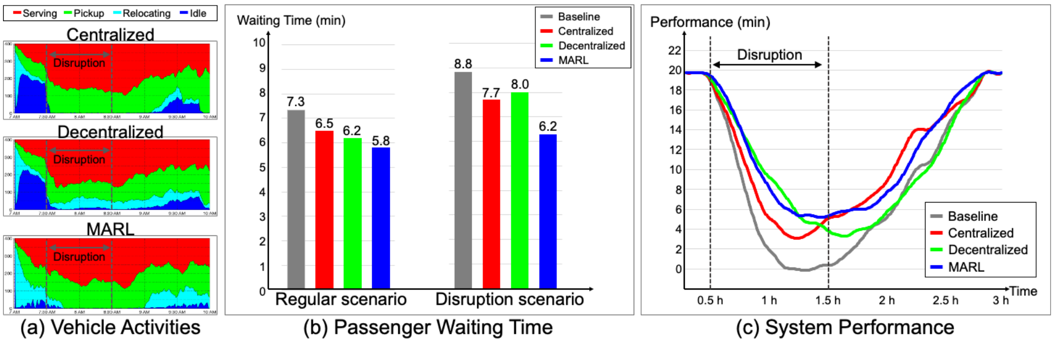

Figure 2 – *Comparison results between rebalancing approaches*

DISCUSSION

This study assesses the resilience of rebalancing strategies for RH services in multi-modal transportation systems. The centralized and decentralized approaches have trade-offs in system performance. The designed MARL approach shows intermediate performance while also enhancing overall resilience.

We are currently investigating the impacts of uncertainty and delays in demand prediction during disruptions. It is expected that uncertainty in demand prediction will largely affect system performance. For instance, operators may maintain the RH service system based on regular demand predictions until they are informed of disruptions. The results will be presented at the conference. Additionally, the impacts on users' travel behaviors by different modes will also be evaluated.

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