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En-route transfer-based dynamic ridesharing

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Abstract

In the last few decades, the continuous growth of travel demand increased urban traffic congestion. The situation demands an efficient way of handling resources like roads and vehicles. Parallelly, the advancement of technology proposed more innovative forms of shared mobility, such as flexible pods. These autonomous, modular vehicles possess the unique capability to autonomously merge and split during their journeys, facilitating en-route transfer of passengers. Formulating a precise mathematical model that comprehensively captures the intricacies of such a complex system is quite challenging. This paper introduces an alternative approach rooted in Reinforcement Learning that circumvents the need for a predetermined mathematical model. Instead, it enables the system to learn its dynamics through interactions with the environment. The primary goal of this research is to acquire an optimized passenger transfer policy. The experimental findings indicate that the transfer-based pod service outperforms private taxi services and Demand Responsive Transport services, boosting vehicle utility by 18% and 8%, respectively. Remarkably, the pod service achieves these gains with only one-third of the vehicles required for private taxis and 13% fewer vehicles than the Demand Responsive Transport service. However, it's important to note that the transfer-based pod service does result in a modest increase in passenger travel time, ranging from 2% to 13%. Therefore, the transfer-based pod service offers a promising opportunity to alleviate traffic congestion while accepting a compromise on passenger travel times.

Keywords: Shared mobility; Reinforcement Learning; passenger transfer; Double Deep Q-Network, future urban transportatio

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1. Introduction

Urban transportation and mobility are facing challenges due to the increasing traffic. Its impact on the environment, economy, and social life is also significant. The European Commission report shows that European cities are affected by traffic-related productivity loss, higher road transportation, and fuel costs. Congestion is mainly located in and around urban areas and costs nearly EUR 100 billion, nearly 1% of the EU's GDP, annually (Christidis et al., 2012). The congestion issues are also prevalent in other developed and developing countries (Bashingi et al., 2020). Among the different transport options, public transport provides a cheaper, environment-friendly service as it efficiently uses vehicle space and serves many passengers at the same time. Hence, it reduces the chance of traffic congestion. However, public transport generally takes longer travel time than private transport and compromises passengers' travel comfort.

Demand Responsive Transport (DRT) combines the features of public and private transport services and offers a demand based shared flexible mobility service. DRT service improves mobility, especially in low-demand areas where public transport is not frequent. However, the DRT vehicles are bound to visit all the drop-off locations corresponding to their pick-ups. The flexible modular pods[1] can overcome this limitation of DRT by allowing en-route transfer. First, the pods pick up passengers from pickup locations. Then while traveling, based on the opportunity, pods can join on the city roads to facilitate passenger transfer. Finally, the pods split to reach corresponding drop-off locations. The characteristics of modularity and en-route transfer can optimally utilize vehicle capacity, and hence, it can also cut down travel cost and traffic. It also avoids the hop-on, hop-off hassles and corresponding transfer time.

Researchers proposed different mathematical modeling to represent the pod's mobility. Guo et al. (2017) proposed an analytical stochastic and dynamic model to optimize transit service switching. Chen et al. (2020); Dai et al. (2020) designed the modular transits considering vehicle dispatch headway and capacity as decision variables. Zhang et al. (2020) considered pods only to serve the first and last miles. Here, the pods connect local passengers to long-distance transport services. Dakic et al. (2021) developed an optimization model that determines the optimal service frequency at which the conventional and modular buses should dispatch. Few other research (Chen and Li, 2021; Shi and Li, 2021; Gong et al., 2021; Pei et al., 2021; Hannoun and Men´endez, 2022) investigated the use of pods with a variable capacity to achieve optimal operations. Unlike previous mathematical formulations, this work proposes a model-free RL-based approach that learns system dynamics by interacting with the environment.

In the last few years, the model-free approach of RL has become popular and applied in many fields. Some research related to passenger pickup and dropoff service have already shown that RL provides an effective way to learn the system dynamics (Oda and Joe-Wong, 2018; Al-Abbasi et al., 2019; Singh et al., 2021; Haliem et al., 2021) without developing mathematical models. MOVI (Oda and Joe-Wong, 2018) used a distributed model-free approach to address the passenger pickup and drop-off problem. Here, Deep Q-Network (DQN) based framework is used to learn optimal dispatch policy. DeepPool (Al-Abbasi et al., 2019), extended MOVI framework to allow ridesharing of passengers. Later, Multi-Hop Ridesharing (MHRS) is proposed, where passengers can take multiple hops to reach their final drop-off locations (Singh et al., 2021). Other research used a similar model-free approach to combine passenger and good delivery (Manchella et al., 2021b) and to incorporate the pricing model in the system (Haliem et al., 2021; Manchella et al., 2021a). Observing the effectiveness of the model-free RL approach that determines optimum dispatch policy, we decided to use it for transfer-based pod's mobility.

While designing en-route transfer-based passenger transport, deciding when a pod should consider transferring its passengers is crucial. A random transfer decision may increase the pod's travel distance, passenger travel time, and transport complexity. Hence, this work aims to determine in which circumstance a transfer could be beneficial and when a pod should travel independently without any passenger transfer. This work aims to analyze pods' mobility, developed based on the model-free RL framework, and compare it with private transport (taxi) service and transfer free ridesharing (DRT) service in terms of fleet utility, travel distance, and passenger travel time. Accordingly, this paper aims to contribute the following –

[1] NEXT IS NOW, www.next-future-mobility.com, accessed June 2022

• Development of model-free RL framework that represents pods' mobility and passenger transfer.
• Double Deep Q-Networks (DDQN)-based decision model to determine transfer policy; and
• Implementation of RL-based pod's mobility for passengers' pickup and dropoff.

This section provides background and motivation for this work and covers the existing literature on the pod's mobility and application of RL in passenger pickup and drop-off problems. Section 2 presents the framework and the components of our proposed methodology. The implementation of the framework and the experimental details are presented in Section 3. An analysis of the results and the key insights are presented in Section 4. Section 5 concludes the paper.

2. Methodology

This section represents the framework of the transfer policy of modular pods. The pods are considered agents in the RL framework. Although the pods can serve both static and dynamic demands, we considered pods to serve dynamic travel demands in this work. Hence, the pods are not dispatched beforehand predicting the future demand; instead, pods are dispatched based on travel requests. It implies that the pods' movement is dynamic, and their joining and transfer are opportunistic. A pod is inactive while waiting for passengers and active while traveling to pick up, drop off, or transfer passengers. Fig. 1 represents the block diagram of the pod's transfer-based ridesharing strategy. In this work, we assumed that a pod could transfer passengers only once on a trip.

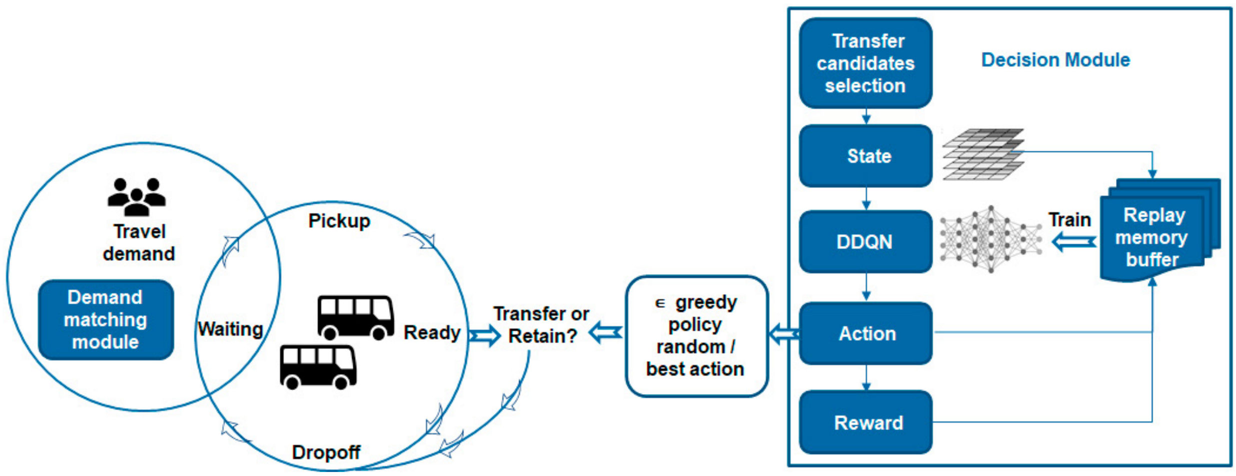


Fig. 1. Modular pod's ridesharing framework

1. *Demand matching module* - Initially, all the pods are inactive and distributed throughout the network. The passengers can raise trip requests at any instance of time. The trip requests are matched and assigned to the nearest available pods having capacity.
2. *Route planning* - After the first assignment of the requests, a pod creates its optimal route plan to pick up and drop off the assigned passengers. Then as per the plan, the pod performs all assigned pickups and becomes Ready to decide its action.
3. *Decision of an action* - The action could be either selecting another pod to transfer the passengers or retaining and dropping them off per the route plan. During the training, this action is decided based on the ϵ-greedy policy. As per ϵ-greedy policy, with $|1-\epsilon|$ probability, a pod selects the best action using DDQN, and with $\epsilon/|A|$ probability, it selects a random action where $|A|$ is the total number of actions.

a) *Transfer candidate selection* - A ready pod p may have several pods in the option to join and transfer passengers. Still, some pods are more promising than others in obtaining benefits or rewards. Those pods are termed candidate pods CP for that ready pod p. The candidate pods CP are identified from inactive pods and among other ready pods whose drop-off locations are similar to p's drop-off locations.
b) *State* - The pod p's and the candidate pods CP's current location and drop-off locations, occupancy, travel time consumed, and active/inactive status are used to create the state information. This state information is fed to DDQN.
c) *DDQN* - DDQN is the implementation of the Double Q-Learning (DQN) with a Deep Neural Network. The policy of selecting an action is learned using the DDQN. We used DDQN as DQN resolves the action value overestimation problem.
d) *Action* - A decision to transfer or retain passengers can be made randomly, or DDQN is used to make the best decision in a given state. The outputs of the DDQN are the actions, i.e., the Q-values of the candidate pods for transferring passengers and the Q-value for retaining the passengers.
e) *Reward* - Based on the action corresponding reward is calculated. In this work, we considered the reward as a function of the number of passengers served, passengers' travel time, passengers' waiting time, number of passenger transfers (hops), pod's trip distance, and pod's utility, i.e., pods' occupancy, and the number of active/idle pods involvement. Among these reward components, the number of passengers served and pods' occupancy have positive impacts, and all other components have negative impacts that act as penalties in the system. In this work, we considered only a single transfer allowed in the trip of a pod. Hence, when we decide to transfer passengers, we recalculate the routes of the pods and calculate the reward components based on the new route. If the decision is to retain passengers, the reward is calculated based on the previous route plan. We calculated the reward as a linear weighted combination of the reward components.
f) *Replay memory buffer* - It stores experiences (state, action, reward, and next-state), then a random subset of these experiences is used to train the DDQN. Experience replay makes the training process fast, stable, and efficient.

3. Experimental Design

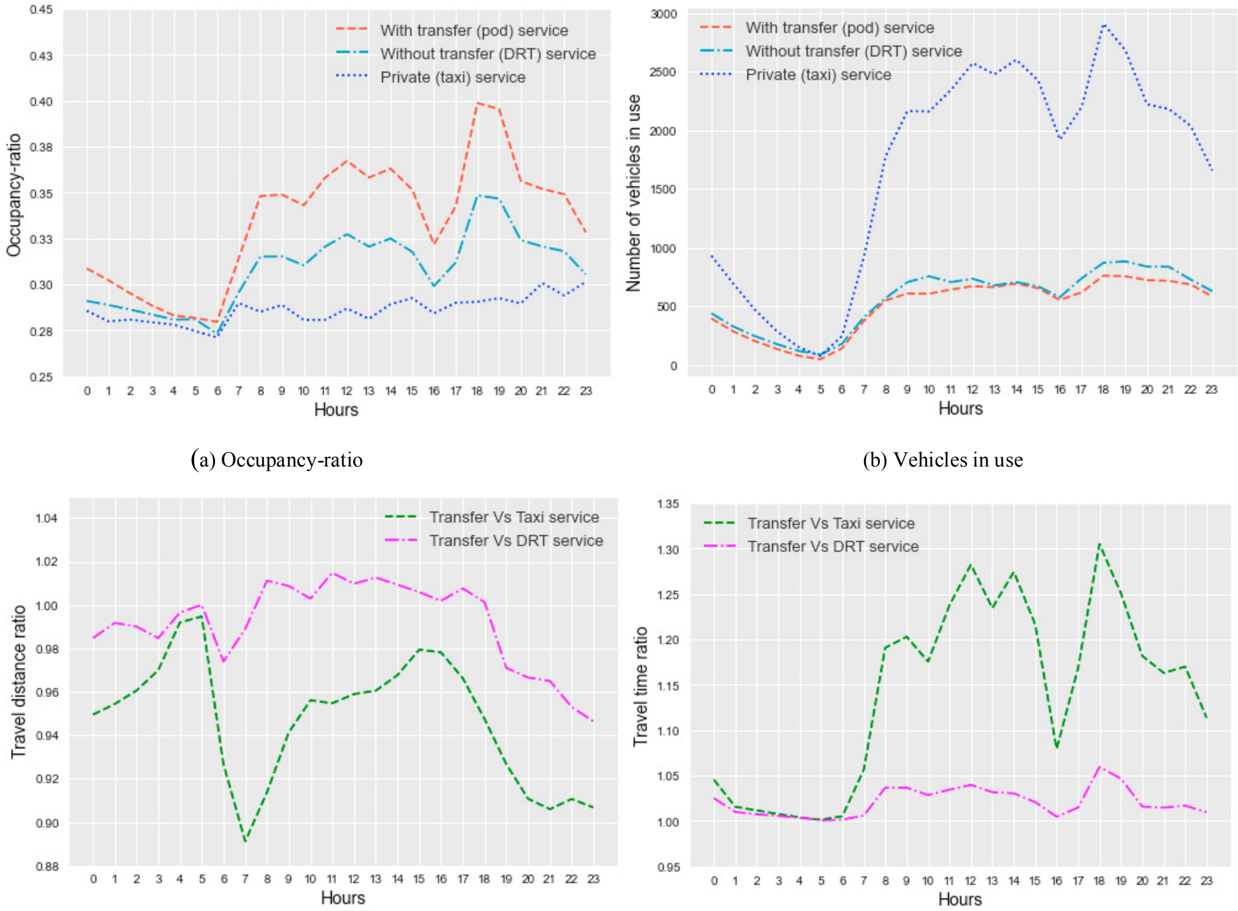
The proposed pod's ridesharing approach is implemented in a spatio-temporal virtual environment. We developed a Python simulator that replicates real-life passenger pick-up and drop-off scenarios. We used a centralized unit to maintain the pods' parameters, such as current location, availability, status, and occupancy. The simulator tracks the incoming trip request at each time step and assigns the requests to the available pods. The decision module decides the actions of all the ready pods. Based on the decision, pods perform actions, and the pods' parameters are updated in the central unit. The pods aim is to maximize the reward while learning the environment using the RL approach.

We used the New York City taxi data for the simulation that contains real taxi trip requests. We extracted trip requests of the Manhattan area and its surroundings during May, 2016. The area is discretized into 10 x 10 grids for easy route calculation. Pod's current locations, pickup-dropoff locations, and transfer points are mapped to the grid representation. We used exact latitude-longitude locations to compute the travel time. To serve this area, 1000 pods are appointed, and each pod can carry a maximum of four passengers. The trip request gets rejected if no pod is available within a seven-kilometer radius.

A ready pod's transfer action is limited to one of the shortlisted pods, or it can also decide to retain its passengers. The decision can is taken randomly or as per the recommendation of DDQN. To learn the environment using the DDQN, we used 21 days of trip data. Each day's data contains approximately 150,000 trip request data. The ϵ value decays from 1 to 0.001 during the learning. The ready pods decide their action in each iteration, and the corresponding reward is calculated. After completing the learning process, we evaluated the transfer-based pod's ridesharing service with the next 7 days trip data. We compared the pod's ridesharing approach with the private taxi service and ridesharing DRT service without transfer. We use the terms *pod* and *vehicle* interchangeably in the continuation of the article. The term *pod* is explicitly used in the context of transfer-based ridesharing, and the term *vehicle* is used in the general context.

4. Results and Discussion

To evaluate the pod's ridesharing service, we used four metrics - vehicle occupancy-ratio, vehicle in use, vehicle travel distance ratio, and passenger travel time ratio. The comparison of pod's ridesharing service with taxi service and without transfer DRT service is shown in Fig. 2.



(a) Occupancy-ratio

(b) Vehicles in use

(c) Travel distance ratio

(d) Travel time ratio

Fig. 2. Comparison between transfer-based pod service, private taxi service, and without transfer DRT service.

a) *Occupancy-ratio* - This metric is defined as the ratio of passenger occupancy multiplied by the trip time with that occupancy and vehicle capacity multiplied by the total trip time. Here, the occupancy can vary from one to four. Fig. 2a represents the hour-wise occupancy-ratio for the transfer-based pod's ridesharing service, without transfer DRT service, and taxi service. It shows that, on average, the occupancy-ratio of transfer-based pod service is 18% higher than the private taxi service and 8% higher than the DRT service. That indicates the transfer-based pod service. utilizes the vehicle space more efficiently compared to the other two services. The occupancy-ratio of taxi service is almost linear throughout. The occupancy-ratio of the pod service and DRT service are similar to the taxi service during the nighttime, 12 am to 6 am, as there are fewer options for ridesharing and transfer. However, the occupancy-ratio improves from 7 am to 11 pm.

b) *Vehicles in use* - This metric represents the average number of vehicles used per hour. Fig. 2b shows that the area can be served by approximately one-third of the vehicles used in taxi service by allowing ridesharing, either DRT or pod-based service. The figure also shows that the pod's transfer-based service can reduce around 13% of vehicle usage compared to the DRT service, specially during rush hours.

c) *Vehicle travel distance ratio* - The travel distance of a vehicle indicates the distance that a vehicle travels to pick up and drop off all the passengers in trips. We represent this metric as a ratio. Here, the transfer Vs taxi travel distance ratio represents the ratio of all vehicles' travel kilometers while using the transfer-based pod's service with respect to the taxi service. And the transfer Vs DRT travel distance ratio represents the distance ratio while using the transfer-based pod's service with respect to the DRT service. A ratio value lower than one indicates that the transfer-based service performs better. Fig. 2c shows that the pods travel 6% less distance on average than the vehicles used in taxi service. The transfer-based service saves the vehicles' travel distances while serving the passengers. But, sometimes, pods need to travel some extra distances to facilitate the transfer operation. As a result, the total average travel distance of pods and DRT vehicles becomes equivalent.

d) *Passenger travel time ratio* - A passenger's travel time is the duration of a passenger's pick up till the passenger's drop off. This metric is also represented as a ratio. The transfer Vs taxi travel time ratio represents the ratio of passengers' travel time while using the transfer-based pod service with respect to the taxi service. And the transfer Vs DRT travel time ratio represents the time ratio while using the transfer-based pod's service with respect to the DRT service. Fig. 2d shows that passengers' travel time increases while using the pod service by 14% on average compared to the taxi service and 2% compared to the DRT service.

5. Conclusion

This research studied a new ridesharing approach of modular, flexible pods that allow en-route transfer of passengers while traveling. This work used modular pods for passenger pick-up and drop-off service and analyzed their impact. We proposed the RL-based framework to represent the pod's mobility and aimed to learn the pod's optimum transfer policy. During training, the pods learned when and to which pod, passengers can be transferred to maximize the reward. Finally, the transfer-based pick-up and drop-off service is compared with the private taxi service and without transfer DRT service.

The experimental results show that the transfer-based pod service would reduce congestion by efficiently utilizing the vehicle space and reducing the number of vehicles on the road, especially during rush hours. On the flip side, the transfer-based pod service increases passengers' travel time which may require compensation like, adjustment of the travel fare or providing an incentive to the passengers. Regarding vehicles' travel distance, the performance of transfer-based pod service and without transfer DRT service is equivalent. Therefore, policymakers need to adapt a more appropriate service on a case-by-case basis. The service should be chosen based on the objective, like reducing congestion or travel time or improving travel comfort.

The transfer-based pod service is a futuristic concept, and the real-time decision to transfer the passenger to another pod has practical and operational implications. The primary idea is to inform passengers regarding their upcoming transfers through the mobile app. This research limits its scope to propose a model-free approach to represent the pod's movement and optimize the transfer operations. As a performance metric, this research has considered vehicle occupancy-ratio, number of vehicles in use, vehicle travel distance ratio, and passenger travel time. In future research, we aim to represent the pod's service using a mathematical optimization model and analyze the pod's mobility with additional metrics like passenger waiting time, number of transfers, and vehicle trajectory. Our future research also aims to implement and analyze complex scenarios like pod's multi-transfer operations.

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