Robust Matching-Integrated Vehicle Rebalancing in Ride-hailing System with Uncertain Demand

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1. Introduction

With the rapid growth of the mobility-on-demand (MoD) market in recent years, ride-hailing companies have become an important element of the urban mobility system. There are two critical components in the operations of ride-hailing companies: driver-customer matching [1] and vehicle rebalancing [2, 3, 4, 5].

While rebalancing and matching are often treated as separate operations in the literature [6], both problems relate to dispatching idle vehicles, either to pick up customers or to increase supply in areas with high expected demand. A common objective for the driver-customer matching problem is minimizing the vehicle miles traveled (VMT) and unsatisfied requests [7, 8] while the primary objective for the vehicle rebalancing problem is minimizing the VMT and a functional term measuring the system-wide service availability for future demand [2, 3, 4].

The overall goal for improving the system-wide service availability for incoming customers is to minimize the number of unsatisfied requests, which coincides with the objective of the driver-customer matching problem. The functional term in the objective of the vehicle rebalancing problem can therefore be treated as an approximation to represent the number of unsatisfied requests. The coincidence of objectives offers us opportunities to integrate rebalancing and matching problems.

In this paper, we propose the matching-integrated vehicle rebalancing (MIVR) model where the area partitioning method is retained and the matching component is modeled at an aggregate level. The performance of vehicle rebalancing algorithms depends on accurate future demand estimations. The rebalancing decision generated by the MIVR model compensates for inaccurate future demand estimation by harmonizing vehicle pickup distance across different demand profiles. To further protect the vehicle rebalancing decisions against demand uncertainty, we introduce robust optimization (RO) techniques to construct a robust MIVR model. A problem-specific uncertainty set is established to better reflect the uncertainty within ride-hailing demand.

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In short, the ride-hailing matching process and RO techniques can be incorporated into the rebalancing procedure to produce better vehicle rebalancing decisions for platforms when facing demand uncertainty. The contributions of this paper can be summarized as follows:

- Proposing the MIVR model to incorporate the driver-customer matching component into vehicle rebalancing problems for the first time, to the best of authors' knowledge.
- Proposing the robust MIVR model to consider demand uncertainty and designing problem-specific uncertainty sets to better reflect the inherent demand uncertainty in the ride-hailing system.
- Demonstrate the performance improvements of the MIVR model and the robust MIVR model with real data from New York City (NYC).

2. Methodology

In this paper, we formulate a mathematical program for the MIVR model. The MIVR model is solved in a rolling-horizon manner, where decision variables are determined repeatedly at the beginning of each time interval. At the beginning of time interval k, κ future time intervals are incorporated in the MIVR model, and only the vehicle rebalancing decisions of the current time interval k are implemented. When proceeding to the next time interval, vehicle locations are observed and updated as the input for the MIVR model. The study region is partitioned into n sub-regions, each sub-region i has an estimated demand $r_i^k \geq 0$ at time k.

The MIVR model introduces the driver-customer matching component into the vehicle rebalancing problem by considering interzonal matchings based on estimated demand. Within a time interval k, the vehicle rebalancing phase happens at the beginning of the interval and the driver-customer matching phase is conducted at the end of the interval. The decision variables for the MIVR model are $x_{ij}^k \geq 0$, denoting the number of idle vehicles rebalanced from sub-region i to sub-region j at time k, and $y_{ij}^k \geq 0$, indicating the number of customers in sub-region i matched with vehicles in sub-region j at time k.

The objective for the MIVR model is minimizing the number of unsatisfied requests and the total vehicle travel distance, which consists of vehicle rebalancing distance and vehicle pickup distance.

By incorporating matching decisions within the vehicle rebalancing problem, the model also considers future matching distance in addition to the rebalancing distance, leading to "smarter" rebalancing decisions. Essentially, the MIVR reduces the cost of inaccurate demand estimation when rebalancing idle vehicles. Meanwhile, the MIVR model is a forward-looking model by incorporating κ future time intervals into the model.

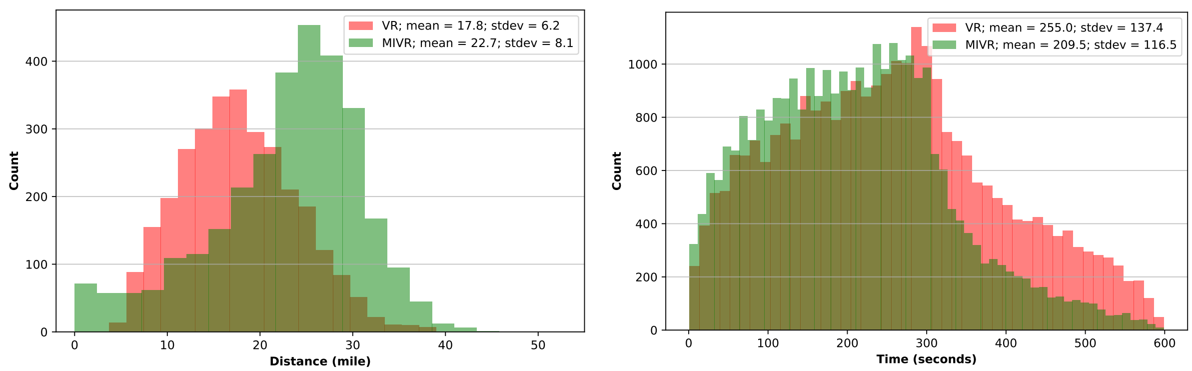
The estimation of the future demand r_i^k is crucial for vehicle rebalancing problems in ride-hailing systems. To further protect the rebalancing decision against demand uncertainty, we introduce the robust optimization technique to establish the robust MIVR model.

The uncertainty set for the robust MIVR model is constructed from the intersection of two different sets. The first uncertainty set imposes upper and lower bounds between estimated regional demand and the historical average regional demand at each time interval. The second uncertainty set limits the total offset in the sum of the demand during a time interval across all sub-regions.

3. Results

To compare the MIVR model with an independent vehicle rebalancing (VR) model, we construct a real-time ride-hailing simulator. To justify the benefit of introducing the robust optimization technique into the vehicle rebalancing problem, an efficient numerical approach is designed to evaluate robust solutions and compare the nominal MIVR model with the robust MIVR model. The study area used in the experiments is the island of Manhattan in NYC. We used the high-volume ride-hailing trip data collected by the NYC Taxi and Limousine Commission [9] as the demand data.

When comparing the MIVR model with the baseline VR model, we found that the MIVR significantly reduces the number of unsatisfied requests by redistributing more vacant vehicles. Meanwhile, the number of customers with longer wait times is reduced in the MIVR model. Under the base case scenario with 3000 vehicles across a 3-hour simulation period, the MIVR model satisfies 6.4% more requests, reduces wait time for customers by 17.9% on average and increases total VMT by 12%. The results are shown in Figure 1.



(a) Vehicle rebalancing distance distribution

(b) Customer wait time distribution

Figure 1: Simulation results

ρ \ Γ	0	1	2	3	4	5	6	7	8	9	10
0.1	15.18	13.49	13.49	13.49	13.49	13.49	13.67	13.28	14.55	12.76	12.94
0.2	13.98	15.19	13.53	15.19	15.19	15.19	14.77	13.98	13.98	13.98	14.01
0.3	14.11	14.11	14.11	14.04	13.91	13.91	14.11	14.11	14.11	14.04	13.82
0.4	10.97	13.32	13.32	13.32	13.32	13.32	13.32	13.32	13.32	13.32	13.32
0.5	12.81	12.77	12.81	12.77	12.81	12.81	12.81	12.81	12.81	12.81	12.81
0.6	10.59	7.98	7.98	7.98	10.59	10.59	10.99	10.59	10.59	10.99	7.15
0.7	8.8	8.8	8.8	9.56	9.56	9.56	8.8	8.8	9.56	9.56	9.56
0.8	8.55	8.55	7.08	8.04	8.04	8.04	8.55	8.55	8.04	6.87	8.55
0.9	8.34	5.2	3.84	3.84	4.09	8.06	4.09	3.84	6.44	6.44	8.06
1.0	3.75	6.75	4.25	6.75	4.47	4.25	4.25	4.25	8.16	8.16	8.16

Table 1: Percent improvement in objective value for robust MIVR over the nominal MIVR for different levels of uncertainty. Scenarios with the largest improvement are colored in the table.

The performance of the robust MIVR model is tested for different levels of uncertainty. Under sufficient supply for a demand profile, the robust MIVR model outperforms the nominal MIVR model for all values of ρ and Γ, which determine the level of uncertainty. Results are shown in Table 1. When a limited supply of vehicles is available, the improvement of introducing robustness into the MIVR becomes marginal. Given an appropriate choice of uncertain parameters, the largest increase in the objective value is around 1% compared to the nominal solution.

4. Conclusion

This paper shows how internalization of matching costs can be used to protect rebalancing decisions against demand uncertainty and improve the efficiency of ride-hailing operations regarding customers, and under what conditions the proposed method is beneficial. Furthermore, it illustrates how robust optimization complements the MIVR model by further limiting the risk of increased cost due to incorrect demand estimations. Ride-hailing service operators should consider adopting the robust MIVR model for improved customer outcomes, such as wait time and unsatisfied requests, and reduced costs for operators.

The main limitations of this study are a result of approximations that were necessary given limited data availability. We are only able to model trips aggregated to the zonal level. Also, we lack trajectory data that would be needed to estimate vehicle transitions across time intervals. The model could be improved if these data were made available.

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