Optimizing Shared Mobility: A Penalized Column Generation Model for Peer-to-Peer Ride-Sharing

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1 INTRODUCTION

Urban areas are increasingly struggling with traffic congestion, environmental degradation, and parking shortages, largely driven by the extensive use of low-occupancy personal vehicles, which average only 1.45 riders per car in Europe (European Environment Agency, 2022). These inefficiencies not only worsen traffic but also cause significant economic losses, reaching nearly 1% of the EU's GDP (European Commission, 2022). As urbanization continues, the demand for innovative transportation solutions becomes more urgent (Bala *et al.*, 2023).

Peer-to-peer (P2P) ride-sharing is a promising solution to some of these urban mobility challenges. This model allows private vehicle owners to offer rides to passengers heading in the same direction, helping to reduce vehicle numbers on the road, lower emissions, and decrease transportation costs for users (Gupta & Shanbhag, 2021). The effectiveness of such a system, however, depends on designing a dynamic pricing model that incentivizes both riders and drivers. Riders expect lower fares in exchange for shared travel, while drivers seek additional revenue for longer or more complex trips (Mo *et al.*, 2023).

Various dynamic pricing models have been explored, taking into account factors like trip length, travel time, and rider preferences (Agarwal *et al.*, 2022). However, many existing models fail to adequately consider real-time traffic conditions and user-specific fare limits, which are crucial for successful adoption (Nourinejad & Roorda, 2016). In response, this paper introduces a novel pricing model for P2P ride-sharing, which adjusts fares based on travel distance, number of passengers, and traffic conditions. The model encourages ride-sharing by reducing the fare per rider as the number of participants increases, thus aligning the interests of both riders and drivers. A significant challenge in P2P ride-sharing lies in real-time rider-driver matching, where the system must handle dynamically changing conditions and user demands. To address this, we propose a Penalized Column Generation algorithm, which optimizes the matching process by balancing driver revenue with rider preferences and fare limits. This algorithm efficiently computes high-quality assignments while handling the complexity of real-time operations (Alisoltani *et al.*, 2022).

The effectiveness of the proposed system is evaluated using the MATSim platform, which simulates the dynamics of urban transportation networks. We applied the model to the city of Lyon, France, assessing the impact of P2P ride-sharing on reducing traffic congestion and improving transportation efficiency.

In summary, this research contributes to the field by: 1) Developing a dynamic pricing model that adjusts fares based on travel distance, passenger count, and traffic conditions. 2) Introducing a Penalized Column Generation algorithm for efficient rider-driver matching in real-time. 3) Using MATSim simulations to evaluate the P2P ride-sharing system's impact on urban mobility under real-world conditions.

2 Methodology

Our study proposes a dynamic P2P ride-sharing system that optimizes the assignment of riders to drivers, balancing both rider preferences and driver incentives. The system integrates a pricing mechanism and a column generation-based optimization algorithm to ensure efficient ride-matching while accounting for multiple constraints including fare limits, vehicle capacities, and travel time.

In the P2P ride-sharing framework, individuals are divided into two groups: drivers and riders. Drivers use their personal vehicles to transport riders, while riders submit ride requests via a digital platform. Each ride request includes the following details: origin and destination locations, latest arrival time, number of seats required, and maximum allowable fare. The ride-sharing platform's primary task is to match riders with drivers based on these criteria, ensuring that the assignments optimize vehicle utilization and minimize total travel costs. The ride-sharing system operates in discrete time intervals, where ride requests are aggregated and assigned to available drivers at the beginning of each time window. The system matches drivers and riders in real-time and considers various factors including travel distance, time windows, vehicle capacity, and fare limits. The assignments are recalculated periodically to incorporate new requests and changing traffic conditions, ensuring an adaptive system that can efficiently respond to real-time urban mobility needs. The key challenge is to efficiently assign riders to drivers such that both driver revenue and ride-sharing efficiency are maximized. We formulate the problem as a mixed-integer programming (MIP) optimization problem. The goal is to maximize the overall revenue for drivers, calculated as the total fares collected from riders minus the drivers' total travel costs. The optimization also takes into account a penalty function, which is applied if the fare assigned to a rider exceeds their specified maximum fare limit. This results in a soft constraint model, where fare violations are minimized but allowed within certain bounds.

The objective function aims to maximize the total revenue for all drivers while minimizing penalties due to fare violations. To achieve this, the assignment of riders to drivers considers the following: 1) Fare limits: riders specify a maximum fare they are willing to pay, and the system tries to assign fares below or equal to this limit. 2) Vehicle capacity: each driver has a capacity limit based on the number of seats in their car. Multiple riders can share a vehicle, but their combined seat requirement must not exceed the vehicle's capacity. 3) Time windows: riders have specified the latest arrival times, and the system must ensure that they are dropped off before these deadlines. 4) Maximizing shared rides: the system encourages shared rides to reduce the number of vehicles on the road and improve overall urban mobility.

To ensure fairness and efficiency in the P2P ride-sharing system, a dynamic pricing model is implemented based on the concept of shareability defined in Alisoltani *et al.* (2022). The fare for each rider is determined based on the travel distance and the number of shared riders. The dynamic pricing scheme adjusts fares according to two possible sharing scenarios:

1. Shareable-First-In-First-Out (FIFO): In this scenario, riders are picked up and dropped off in the order they were added to the system. The fare for each rider is computed based on the portion of the shared ride they contribute to, with a reduced cost for shared segments.

2. Shareable-First-In-Last-Out (FILO): In this scenario, the drop-off order is reversed, where the last rider picked up is the first to be dropped off. The pricing is adjusted to reflect the additional travel time and distance for each rider.

A P2P ride-sharing trip, starting from the driver's origin and ending at the driver's destination, can involve different combinations of these two scenarios. Using Equation 1, we can derive the trip fare for rider n, considering all possible sharing scenarios:

$$F_n = P_{Fixed} + P_{distance}(y^n_{\mathrm{O}_n D_n}.TD_{\mathrm{O}_n\mathrm{D}_n} + \textstyle\sum_{ij\in L, i,j\neq \mathrm{O}_n,\mathrm{D}_n} \frac{y^n_{ij}.TD_{ij}}{N^{ij}_o}) \tag{1}$$

Where P_{Fixed} is the fixed cost each rider pays, P_{distance} is the price per distance unit, TD_{ij} is the distance between each two stops i and j, L is the set of links, O_n and D_n are the origin and destination points for rider n, N^{ij}_o is the number of onboard riders when the driver passes link ij, and $y^m_{i,j}$ is a binary variable that shows if driver m transports a rider from point i to j.

This dynamic pricing model ensures that as more riders share a ride, the per-rider fare decreases, making ride-sharing an attractive financial option. It also balances driver incentives by ensuring that their revenue is maximized based on the total number of passengers and the total travel distance.

To solve the optimization problem efficiently, we use a Penalized Column Generation approach, which is suitable for large-scale ride-sharing assignments. This algorithm iteratively generates and evaluates potential solutions, adding the most promising combinations of drivers and riders to the model at each step. At the start of each assignment period, an initial set of assignments (or "columns") is generated based on the current set of ride requests. These initial assignments are evaluated based on their feasibility in terms of time, capacity, and fare limits. During each iteration, the algorithm identifies promising new assignments, which involve matching additional riders to drivers. The system checks whether these new assignments improve the overall solution by maximizing driver revenue and minimizing fare violations. If a rider's assigned fare exceeds their maximum allowable fare, a penalty is added to the objective function. The algorithm balances maximizing driver revenue with minimizing these penalties. The system optimizes the assignment of riders to drivers, ensuring that constraints such as vehicle capacity and time windows are met. The algorithm continues iterating, generating new columns and refining the solution until it converges to an optimal or near-optimal solution. Once the best possible assignments are identified, they are finalized, and the drivers and riders are notified of their ride-sharing arrangement. The process is repeated for each assignment period.

The performance of the proposed P2P ride-sharing system was tested using real-world urban traffic data from the city of Lyon, France. We utilized the MATSim simulation platform to simulate the dynamics of urban mobility, accounting for real-time traffic conditions, vehicle routing, and ride-sharing behavior. The simulation evaluates the impact of our dynamic pricing model and column generation algorithm on system efficiency, including metrics such as the total number of shared rides, driver revenue, and rider satisfaction.

3 Experiments and Results

To evaluate the performance of the proposed P2P ride-sharing system, we used data from the Lyon network, focusing on 24,046 eligible travelers for ride-sharing out of a total of 97,356 commuters. The remaining travelers continued to use personal cars. The study tested various scenarios by increasing the number of drivers among morning commuters.

The simulation used different fare limits based on public transport costs, traditional taxi fares, and rider preferences. Taxi fares in Lyon served as a baseline, with a fixed fee of 7.10 € and 1.62 €/km (Taxi Lyon, 2023). A penalty factor α, ranging from 0.5 to 0.9, was applied to account for fare violations, ensuring the fare structure remained aligned with rider expectations.

The results, summarized in Table 1, compare the baseline scenario (no ride-sharing) with varying numbers of drivers. As the number of drivers increased, the average revenue per driver remained stable at around 22.5 €, while the average fare per rider increased only slightly. In Scenario 5, with 7,370 drivers, the matching rate reached 73.6%, with 12,279 riders matched. Scenario 7, with 11,055 drivers, achieved a matching rate of 98.2%, significantly reducing reliance on personal car trips.

Table 1 – *Simulation Results - Drivers and Riders*

Scenario	Drivers			Riders		
	Number	Matched	Rev/Trip (€)	Number	Matched	Fare/Trip (€)
1	0	0	0.00	24046	0	0.00
2	1500	1410	22.42	22546	2602	12.15
3	1842	1725	22.51	22204	3198	12.14
4	3685	3393	22.64	20361	6245	12.30
5	7370	6701	22.79	16676	12279	12.44
6	8790	7685	22.66	15256	13932	12.50
7	11055	7110	22.49	12991	12763	12.53

Table 2 shows that as ride-sharing adoption increased, the total number of personal car trips and total travel distance decreased, reducing traffic congestion and environmental impact. In Scenario 7, total car trips dropped by 17.16%, and total distance decreased by 8.0%.

Table 2 – *Simulation Results - Personal Cars*

Scenario	Personal Cars		All Cars	
	Trips	Tot Dist (km)	Tot NumTrips	TotDist (km)
1	97356	849909	97356	849909
2	93254	817074	94664	835491
3	92316	809470	94041	831939
4	87426	770290	90819	815653
5	77707	691690	84408	783631
6	74634	665571	82319	773441
7	73538	657514	80648	781961

Overall, these results demonstrate the effectiveness of the P2P ride-sharing system in reducing personal car usage, improving traffic efficiency, and offering economic benefits to both drivers and riders.

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