Optimizing MaaS for Commuters: Exploring Ride-Pooling Potentials

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Short summary

Individual commuter traffic, characterized by low car occupancy and significant emissions, offers opportunities for ride-pooling as a sustainable alternative. This paper introduces a methodology that integrates a dynamic demand model using agent-based simulations with ride-pooling service and fleet optimization. The approach captures scenario-specific demand variations and enables detailed fleet simulations while exploring service parameters, including pricing, detour limits, and service constraints. It couples service parameters and service demand, while optimizing mobility services within a large search space. A case study applied in suburban and rural regions demonstrates the methodology's potential to improve pooling efficiency and operational performance. While the results highlight promising opportunities, further enhancements, such as stop-based systems and intermodal integration, are needed to maximize scalability and pooling potential. This dynamic approach provides the foundation for a holistic, commuter-focused ride-pooling service optimization. It addresses demand responsiveness, fleet management, and the diverse objectives of commuters, providers, and transit agencies.
Keywords: Demand modeling, Operations research applications, Optimization, Pricing optimization, Shared mobility.

1 Introduction

Situation of Commuter Traffic

Commuter traffic significantly impacts the transportation system, contributing to around 20% of overall traffic volume in Germany. Approximately 74% of commuting distances are covered by private cars, with a low average occupancy of 1.075 persons per vehicle. This heavy reliance on private vehicles leads to high traffic volumes during peak hours and accounts for 22.4% of total passenger traffic emissions, making it a major contributor to greenhouse gas emissions. Verkehrswende (2022)
Despite these challenges, commuter traffic offers opportunities for mobility service providers. Commutes are repetitive and predictable, enabling the development of efficient, scenario-specific mobility solutions. These patterns allow for stable operating margins and consistent traffic and environmental impacts.
Ride-pooling combines trips from multiple customers into shared rides, increasing vehicle occupancy and utilization. This reduces vehicle kilometers, emissions, and costs for both customers and providers, especially with the usage of autonomous vehicles (AVs), addressing issues in current commuter traffic. Ride-pooling can compete with private vehicles in terms of speed and comfort, connect rural areas lacking public transport, and serve as first-/last-mile mobility, enhancing public transport accessibility in underserved regions Santi et al. (2014); Alonso-Mora et al. (2017); Jian Wen et al. (2018); Engelhardt et al. (2019); Dandl et al. (2021).
Commuter traffic's high trip density, both temporally and spatially, allows ride-pooling to leverage network effects for improved pooling efficiency and system performance Tachet et al. (2017); Engelhardt et al. (2019); Kucharski & Cats (2022).

Challenges in Optimizing Ride-Pooling Services

Optimizing ride-pooling for commuters involves several challenges. The novelty of ride-pooling services in operation means there is limited guidance for its implementation. Scenario-specific factors such as commuter behavior, public transport availability, traffic density, and commuting patterns make it difficult to identify feasible and beneficial use cases. Furthermore, demand prediction holds

another challenge, as little historical demand data exists for ride-pooling services. The demand is interdependent with service parameters, such as pricing models and detour limits, which themselves depend on scenario-specific factors like infrastructure and competition from other modes of transport.
The optimization process involves large search spaces of service parameters that are correlated with the fleet characteristics. Therefore, fleet design must be integrated with service optimization, adding another layer of complexity.
In this paper, ride-pooling potentials for commuter traffic are explored, and a methodology for holistic service optimization with a focus on adaptive demand modeling is presented.

Literature Review

Several research areas are related to the approach in this paper, including demand modeling for ride-pooling systems, the influence of service parameters on demand and performance, and optimization methods involving multiple actors.
Agent-based modeling frameworks using activity-based mode choice, such as MATSim Horni et al. (2016), have proven effective in modeling demand for ride-pooling services. These frameworks simulate individual travel behavior and interactions within the transportation system, allowing detailed scenario-based analysis. Using MATSim, Zwick & Axhausen (2020a,b); Zwick et al. (2021) applied a ride-pooling service in multiple scenarios to explore the influence of different service parameters on performance and environmental impacts. These methods often rely on computationally intensive iterative simulations to adjust demand based on service parameter changes, limiting scalability for large-scale optimization.
Several studies explore the influence of various parameters on service performance and demand by comparing pooled and private trips. Kucharski & Cats (2020, 2022) introduced graph-based methods to efficiently match requests to pooled rides, reducing computational complexity, and investigated occupancy rates under various fare discounts, demand densities, and operational strategies. De Ruijter et al. (2023) studied demand behavior in relation to sharing discounts, delay aversion, and demand distribution. The influence of detours on ride-pooling demand and performance has been studied by Alonso-Mora et al. (2017); Ke et al. (2021). Ride matching, operational strategies, and fleet optimization techniques were investigated by Santi et al. (2014); Alonso-Mora et al. (2017); Kucharski & Cats (2020); Engelhardt et al. (2022).
Efforts have been made to incorporate interdependencies between service parameters in optimizing ride-sharing services and demand. Liu et al. (2019) developed a dynamic demand model that adjusts agent mode choice based on service parameters and optimizes fleet size and fares. Wilkes et al. (2021) emphasizes real-time demand-supply linkage, coupling a travel demand model with ride-pooling optimization to reach equilibrium without iterative simulations. The work of Dandl et al. (2021) examines the interplay between regulators, providers, and customers. A three-level model is optimized, aiming for optimality at each level. Demand is inferred from demand matrices, and a mode choice model is implemented that allows a choice between public transport, private car, and a ride-sharing service.
While existing methodologies have significantly advanced ride-pooling services, a methodology handling holistic ride-pooling service optimization is still needed. This method must capture interdependencies between demand and service parameters while enabling rapid iteration of large search spaces. Scenario-driven, agent-based demand generation needs to be combined with detailed service optimization techniques. In this way, ride-pooling services can be tailored to different contexts, exploring efficient and sustainable mobility solutions for all regions.

Research Goal

The research aims to address critical gaps in ride-pooling optimization by focusing on commuter-specific needs and dynamic demand modeling. Existing studies often rely on static demand models, overlooking the interplay between service parameters and user demand. To overcome this limitation, this study leverages the MATSim simulation framework to conduct agent-based mobility simulations, capturing dynamic demand variations and adapting to scenario-specific changes. A comprehensive optimization framework integrates these simulations with the optimization of service parameters, fleet management, and pricing schemes for ride-pooling services. Additionally, the research evaluates ride-pooling in conjunction with other transportation modes, ensuring realistic estimates of user acceptance. Specific commuter constraints regarding delays and cancellations are considered.
The following section 2 presents the methodology used to achieve these goals, followed by a case

study in section 3, that applies the methodology to a rural and a suburban commuter use case. The simulation results are then presented and analyzed. Finally, the methodology is reviewed, and limitations, further research, and future developments are discussed within the section 4.

2 Methodology

Base Simulation

MATSim is used to run a mobility simulation for the scenario containing all agents from the population. A trip-based discrete mode choice model is used Hörl et al. (2018). All base modes available in the scenario are used for mode choice. This simulation results in a travel time matrix for the simulated traffic network as well as a population containing the daily schedules of the agents. From this population, the base modes and base scores for each trip can be extracted.

Preconditions

To streamline the optimization process and adapt it for commuter traffic, specific preconditions are applied based on the characteristics of commuter trips and the need to reduce computational complexity while maintaining realism.
Pre-Planned Trips: All trips are assumed to be pre-planned, as commuters typically know their schedules in advance. This allows the optimization process to focus on fixed trip schedules without accounting for real-time changes.
No Waiting Time: Given the pre-planned nature of trips, it is assumed passengers experience no waiting time. Services are designed to pick passengers up at the exact planned departure time, and delays at home or work are not perceived as waiting.
Relevant Parameters: Following the absence of waiting time, the ride-pooling service can be described using two key parameters: Price, reflecting cost per kilometer, and Detour, representing the relative increase in travel time compared to a direct trip.
Commute Trips: The analysis includes only commute trips that start at home and end at the workplace (or vice versa), without intermediate stops. This ensures a focus on typical commuter scenarios while simplifying the analysis. This constraint can be released to allow intermediate stops within later research.
Static Travel Times: Fixed travel time matrices are used, allowing computationally intensive tasks to be preprocessed. This significantly reduces optimization time.
Linear Mode Choice Model: Agents choose the mode with the highest score for each trip. Scores are precomputed based on static travel times, eliminating the need for recalculation during the simulation and simplifying decision making.
These preconditions ensure the optimization process remains efficient and focused on commuter-specific requirements while enabling a realistic, holistic evaluation of ride-pooling services.

Demand Generation

Commuter demand is generated using an agent population by adding commutes to the demand database that can be served by ride-pooling, while improving trip utility. An optimization framework, developed for MATSim, evaluates various ride-pooling service configurations by applying a grid search iterating two parameters:

- **Price:** The cost per km in €/km
- **Detour Time:** The time difference needed for each commuter compared to the direct trip

Each trip is routed and scored based on the specific ride-pooling parameters, incorporating price and detour, reflecting the agent's trip utility. This generates a demand database containing trip scores for all service configurations. Comparing ride-pooling scores with base mode scores identifies configurations where ride-pooling outperforms alternatives, determining the minimum requirements for the demand generation. These results are stored in a minimum requirement demand database for further use.

Ride Generation

Feasible shared rides are generated using the ExMAS algorithm Kucharski & Cats (2020), adapted to handle the commuter-specific needs. The algorithm identifies all potential rides that meet the following conditions:

- **Passenger Constraints:** All passenger minimum requirements are satisfied.
- **Ride Structure:** All passengers origins are visited first, followed by all destinations.

This produces a database of viable rides serving all possible requests, while reducing variational complexity and favoring rides with high pooling rates.

Parameter optimization

The optimization process iterates over global service parameters, including pricing schemes, detour limits, and rejection schemes to tailor the ride-pooling service towards the optimization goals. The demand database is filtered to include only requests feasible under these current pricing constraints. Similarly, the rides database is updated to only retain rides that serve these filtered requests while satisfying all detour requirements. This generates the actual demand for the ride-pooling service and the rides that can service this demand, simply by filtering these two datasets.

Mixed-Integer Programming for Matching and Optimization

The Mixed-Integer Programming (MIP) model matches rides to requests, determining which rides to activate and which commuters to reject. The model considers commuter specific constraints such as a commuter rejection rates, as well as fleet size constraints and operational costs.

Variables:

- **Ride Activation:** Binary variable x_r for each ride $r \in R$, where R is the set of all possible rides:
$$x_r = \begin{cases} 1 & \text{if ride } r \text{ is selected,} \\ 0 & \text{otherwise.} \end{cases}$$
- **Commuter Rejection:** Binary variable y_c for each commuter $c \in C$, where C is the set of all individual commuters:
$$y_c = \begin{cases} 1 & \text{if commuter } c \text{ is rejected,} \\ 0 & \text{otherwise.} \end{cases}$$
- **Fleet Size:** Integer variable F representing the number of vehicles:
$$F \in \mathbb{Z}_+$$

Constraints:

- **Commuter Coverage:** If a commuter is accepted ($y_c = 0$), then every request p they make must be served by exactly one ride from the set of rides R_p that can serve the request. If the commuter is rejected ($y_c = 1$), none of their requests can be served. This is formulated as:
$$\sum_{r \in R_p} x_r = 1 - y_c \quad \forall c \in C,\ \forall p \in P_c \tag{1}$$
Here, $P_c \subseteq P$ represents the set of all requests made by commuter c, and $R_p \subseteq R$ is the set of rides that can serve request p.
- **Rejection Limit:** The total number of rejected commuters cannot exceed the allowable rejection rate α, defined as a percentage of the total number of commuters:
$$\sum_{c \in C} y_c \leq \lfloor \alpha \cdot |C| \rfloor \tag{2}$$
where $\alpha \in [0, 1]$ is the maximum allowable rejection rate, and $|C|$ is the total number of commuters.

- **Fleet Size:** The number of active rides at any time t cannot exceed the available fleet size:

$$\sum_{r \in A(t)} x_r \leq F \quad \forall t \in T \tag{3}$$

Here, $A(t) \subseteq R$ denotes the set of rides active at time t, and T represents the set of all relevant time intervals.

Objective Functions:

Two objective functions are considered, each optimized in separate runs:

- **Profit Maximization:** The goal is to maximize the profit:

$$\max\Big(\sum_{r \in R}(\pi_r - c_r)x_r \; - \; c_v \cdot F\Big). \tag{4}$$

Here, π_r represents the income from ride r, c_r represents the operational cost for ride r, and c_v is the fixed cost per vehicle.

- **Fleet Distance Minimization:** The goal is to minimize the total distance traveled by the fleet:

$$\min\Big(\sum_{r \in R} d_r \, x_r\Big). \tag{5}$$

Here, d_r represents the distance covered by ride r.

Outputs of the MIP Model:

The MIP produces the following outputs:

- **Activated Rides:** A list of rides $r \in R$ for which $x_r = 1$, indicating they are selected for service.
- **Fleet Size:** The optimal number of vehicles F required to service the activated rides, ensuring fleet efficiency and cost-effectiveness.
- **Rejected Commuters:** A list of commuters $c \in C$ for which $y_c = 1$, indicating their requests are not served. This helps in understanding the impact of rejection limits and commuter coverage.

By combining a parameter grid search with the MIP optimization, the framework ensures efficient matching of rides to requests while considering commuter and operational constraints optimizing for operator objectives. This approach allows for scalable and scenario-specific ride-pooling solutions tailored to commuter needs. The MIP can be extended for fleet management and pricing optimizations in future research.

3 Results

Case Study

Two commuter scenarios (25% population sample) in Germany, one rural and one suburban, are used to apply the methodology. The rural scenario is characterized by a large number of commuters with varying travel distances, including commutes of up to 80 km to the next major city. The suburban scenario focuses on commutes between a suburban and an urban area. Both cases are characterized by poor public transport connections compared to car travel times.
The base simulation is performed using MATSim, generating a travel time matrix and filtering commuters from the population. The ride-pooling parameter set includes prices ranging from 0.0€/km to 1.0€/km (in 0.05€/km increments) and additional detours ranging from 0% to 100% of direct trip time (in 5% increments). Trip scores for all parameterizations are calculated and compared to base scores, creating the minimum requirements database.
The optimization search space is defined to include pricing schemes, minimum prices, maximum detours, and rejection rates. Four pricing schemes are examined:

- Equal Pricing: All passengers pay the same price per kilometer.

- Detour Pricing: Passengers pay a fixed price per kilometer, discounted by the percentage of their actual detour.
- Personal Pricing: Passengers are charged the maximum price that still improves their score over the trips base score, considering their actual detour.
- Ride-Based Pricing: Rides are priced at the maximum price all passengers served by this ride can pay while still improving their base score, considering their actual detour.

While equal and detour pricing are known in current research, the personal and ride pricing schemes are enabled by the developed demand dataset. For operating costs 0.15€/km and 15€/Vehicle/Day are assumed.

Results

First, the pooling potential and minimized fleet distance, achievable for a ride-pooling service when serving all requests, are simulated. The personal pricing scheme is used with a minimum price set to €0.0/km, generating the maximum demand. Maximum detours are varied. Figure 1 shows the results for both the suburban and the rural scenarios.

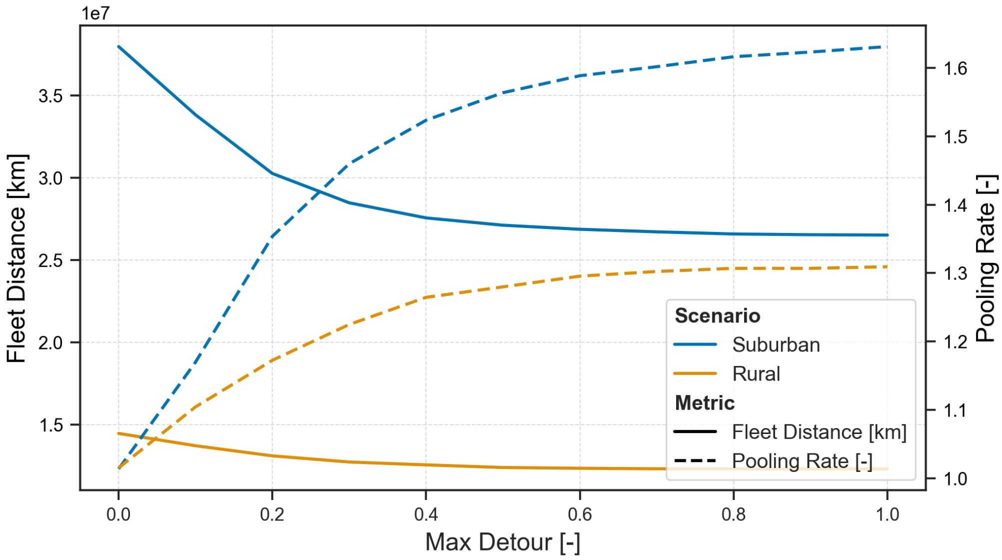

Figure 1: Fleet Distance and Pooling Rate over Maximum Detour. Suburban vs. Rural Scenario.

Both scenarios demonstrate potential for fleet distance reduction. The suburban case shows greater pooling efficiency due to shorter, denser commutes, achieving pooling rates above 1.6 compared to 1.3 in the rural case.
Next, the influence of the price on the demand is examined by fixing maximum detours at 40% of direct trip time. Prices range from 0.0€/km to 1.0€/km, and rejection rates up to 0%, 5%, 10%, and 100% are allowed. Figure 2 presents the results for the suburban scenario.
Higher prices significantly reduce the number of fulfilled requests due to reduced demand. Profits stabilize beyond 0.6€/km. From this point, higher prices cause further declines in (fulfilled) requests without additional profit gains. Increased rejection rates improve profit only up to 0.4€/km.
To compare pricing schemes, detours remain fixed at 40% of direct trip time, prices are iterated, and the rejection rate is set at 5%. Figure 3 shows results for the rural scenario.
As expected, the personal pricing scheme performs best, particularly at lower prices. As prices increase, ride-based pricing becomes equivalent. Detour pricing underperforms compared to equal pricing up to 0.4€/km, after which it is able to achieve higher profits while also serving more requests.

Discussion

The results demonstrate that the proposed methodology effectively optimizes ride-pooling services across multiple scenarios. It captures the interdependencies between service parameters and demand while allowing for holistic service optimizations in a scenario-based manner. In the presented

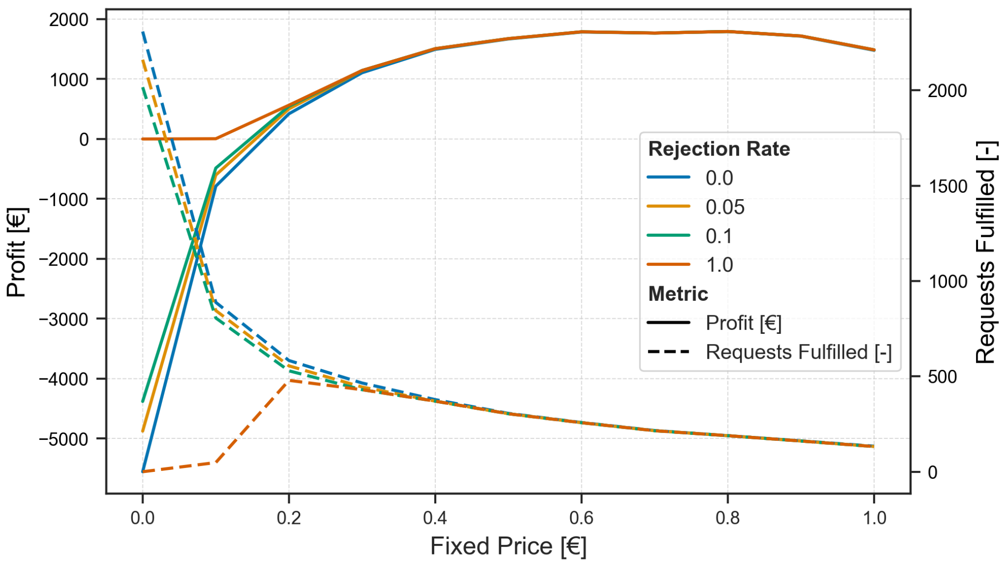

Figure 2: Profit and Fulfilled Requests over Price per km. Suburban Scenario.

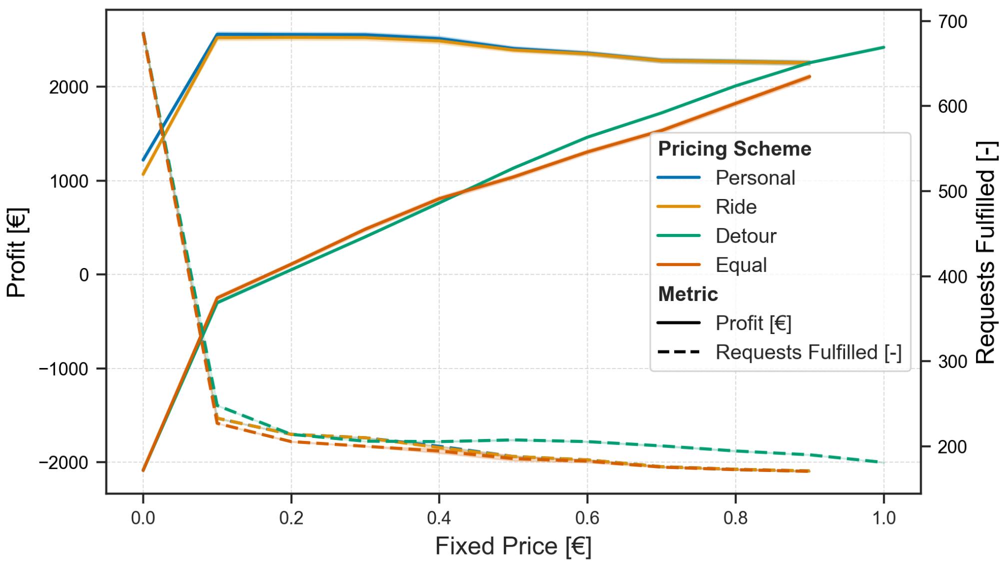

Figure 3: Profit and Fulfilled Requests by Pricing Scheme. Rural Scenario.

simulations, suburban scenarios show higher pooling potential due to shorter, denser commutes. The pricing strategy heavily influences the demand, with diminishing returns beyond 0.6€/km. Personal pricing schemes maximize profit but are not very applicable in reality. Detour pricing performs well at higher price levels, offering a viable option for real-world usage.
Matching a scenario with several thousand requests can be archived on a regular PC in seconds, allowing iteration of large search spaces. This enables providers to identify promising markets and adjust ride-pooling service configurations in the early stages of development.

4 Conclusion

This study presents a methodology that bridges the gap between detailed mobility simulations and computationally efficient, high detail fleet optimization for ride-pooling services. By integrating a dynamic demand model, responsive to changes in service parameters, it captures the influence of critical supply parameters, such as pricing schemes, detour limits, rejection rates, and minimum prices, on the service demand. The methodology highlights rural inclusion by comparing rural and suburban scenarios and emphasizes commuter requirements, such as consistent rejection schemes

and unique delay constraints, that were not considered in previous studies.
The results highlight the potential of ride-pooling services to mitigate the negative impacts of commuter traffic while maintaining viable business opportunities for providers. The findings demonstrate higher pooling efficiency in suburban areas due to shorter and denser commutes, while rural areas benefit from reduced travel costs and improved accessibility. However, the current configuration, focused on door-to-door services, reveals limited pooling potential. To address current limitations and further enhance pooling efficiency, future work will focus on integrating stop-based systems and intermodal transport solutions. Stop-based services hold significant potential for increasing pooling rates and reducing operational costs, while intermodal integration can seamlessly connect ride-pooling with the public transport, enhancing accessibility and sustainability. This methodology also enables future refinements in fleet optimization, such as advanced vehicle scheduling based on ride sequencing and dynamic pricing schemes tailored to time-based or cluster-specific demand patterns. These extensions, combined with dynamic pricing strategies and policy measures, provide a robust foundation for optimizing commuter-focused ride-pooling services across rural, suburban, and urban contexts.

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