Stochastic Optimization under Supply Uncertainty for Multimodal Trip Planning Based on Demand Prediction

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1 INTRODUCTION

The growing integration of shared micromobility systems, such as e-scooters and bikes, with public transport services has opened up new opportunities for optimizing multimodal trip planning (Oeschger *et al.*, 2020). One of the major concerns faced by passengers is the uncertainty of vehicle availability at different locations, which can vary significantly due to uncertain demand influenced by factors such as time of day and location type (e.g., shopping malls, schools, residential areas), as shown in Figure 1. A multimodal transport platform, like Mobility as a Service (MaaS), aspires to provide reliable trip suggestions. Therefore, this study proposes a multimodal trip planning approach to the platform to ensure accessible micromobility service to passengers and promote multimodal transport.

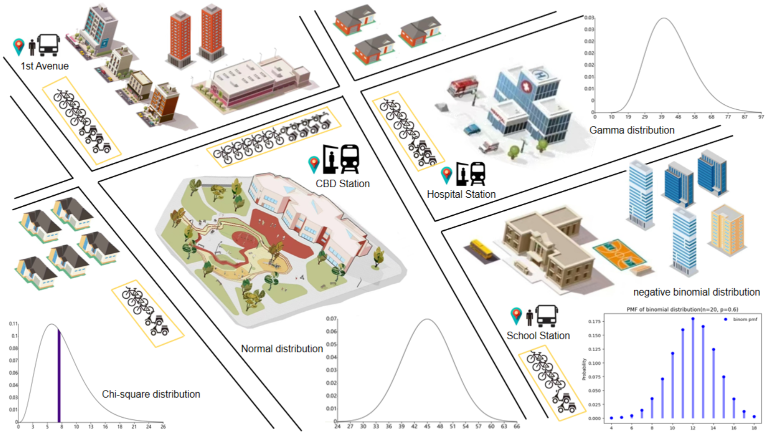


Figure 1 – *Temporal variations in heterogeneous demand distributions across different urban areas*

In the existing literature, scholars predominantly focus on stochastic optimization to ensure reliability (Ding *et al.*, 2024), with limited research addressing the integration of prediction and stochastic optimization. Unlike approaches that rely solely on stochastic optimization with static historical data, incorporating prediction allows for the adaptation to changing conditions by capturing trends and external factors (e.g., seasonality and weather), making the optimization more responsive and effective in dynamic environments, especially when data is limited or variable. To tackle operational challenges arising from demand and supply uncertainties, we propose a stochastic optimization framework that first predicts demand, which is then used to estimate supply uncertainty and optimize trip planning, ensuring passengers can reliably plan trips using both micromobility and public transport.

2 Methodology

The methodology incorporates demand prediction and stochastic optimization for reliable real-time trip planning under supply uncertainties, as illustrated in Sections 2.1 and 2.2.

2.1 Demand prediction of shared micromobility

In a shared mobility service without active rebalancing, fleet availability is driven by the intensity of pickup and dropoff requests, which tends to follow periodic patterns based on the functions of different areas. To enhance prediction accuracy, points-of-interest (POI) data are considered, capturing the characteristics of locations such as shopping centers, universities, and residential areas, each of which may exhibit distinct supply behaviors. Additionally, short-term demand for shared micromobility services is closely influenced by the local weather conditions. We propose a transformer-based model to predict the probabilistic demand of shared micromobility at various locations using multivariate contextual inputs. The output is conditional probability distributions, denoted as $P(\hat{p}_i^{t,t+1}|X^t)$ and $P(\hat{d}_i^{t,t+1}|X^t)$, which represent the pickup and dropoff demands at location i in the next time interval, given the multivariate input values $X_t \in \mathbb{R}^m$.

2.2 Stochastic optimization for multimodal trip planning under supply uncertainty

Using real-time demand predictions of shared micromobility, our framework then estimates the supply uncertainty and generates suggested trip for each passenger when the request is received. These alternatives may include either a single mode (e.g., only shared micromobility) or multimodal transport options combining micromobility with public transport. The goal is to ensure that each recommended trip has a high probability of vehicle availability and reduce the uncertainty faced by passengers.

To achieve this, we employ stochastic optimization techniques, i.e., Chance Constrained approach, to model and mitigate the supply uncertainty. By incorporating the supply uncertainty into the optimization process, our approach generates trip recommendations that maximize the likelihood of vehicle availability for passengers, ensuring a reliable multimodal experience. At each time step $t \in T$, the objective is to minimize the cost of using multimodal transport:

$$F = \sum_{r \in R} \sum_{k \in K} \sum_{(i,j) \in A} c_{ij}^k x_{ij}^{kr} \tag{1}$$

$$c_{ij}^k = \alpha^k + \beta^k \tau_{ij}^k + \gamma^k d_{ij}^k \tag{2}$$

where $(i,j) \in A$ represents the routes, $k \in K$ denotes the vehicles, and c_{ij}^k specifies the cost of using vehicle k on route (i,j). Multiple vehicles can be utilized to serve the same request. α^k, β^k and γ^k represent a fixed baseline cost, cost parameter related to actual travel time τ_{ij}^k, and cost parameter related to distance d_{ij}^k using vehicle k, respectively. x_{ij}^{kr} is a binary decision variable, equal to 1 if passenger $r \in R$ is assigned to vehicle k on route segment (i,j), and 0 otherwise.

Given that the initial supply $\hat{q}_i^0$ is known, the uncertain fleet availability at location i at time t, denoted as $\hat{q}_i^t$, needs to be restricted by the chance constraint 3:

$$P((p_i^{t,t+1} - d_i^{t,t+1}) \leq q_i^t - (\hat{p}_i^{t,t+1} - \hat{d}_i^{t,t+1})) \geq 1 - \alpha, \ \forall t \in T, \forall i \in N_{\text{micro}} \tag{3}$$

Constraint 3 ensures that the probability of the total number of passengers using micromobility vehicles at location i during time $t+1$ being less than or equal to the available fleet $\hat{q}_i^{t+1}$ is at least $1-\alpha$, for all $t \in T$ and $i \in N_{\text{micro}}$. Here, $p_i^{t,t+1} - d_i^{t,t+1}$ represents the total number of passengers using micromobility vehicles at location i during time interval t to $t+1$, and the supply $\hat{q}_i^{t+1}$ at time $t+1$ equals the current supply q_i^t at time t minus the predicted demand, which is determined by the predicted pickup demand $\hat{p}_i^{t,t+1}$ minus the dropoff demand $\hat{d}_i^{t,t+1}$.

Equation 4 calculates the current supply, which is the supply at the previous time $t-1$ minus the fleet changes due to the pickup ($p_i^{t-1,t}$) and drop off events ($d_i^{t-1,t}$) during the time interval from t to $t+1$.

$$q_i^t = q_i^{t-1} - (p_i^{t-1,t} - d_i^{t-1,t}),\ \forall t \in T, \forall i \in N_{\text{micro}} \tag{4}$$

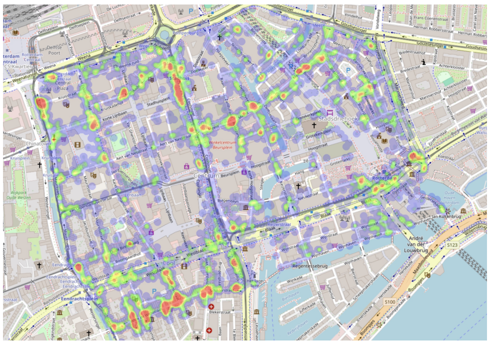
We propose a heuristic algorithm 1 to select the optimal grid for utilizing micromobility considering supply uncertainty. We first determine the appropriate public transport line based on the passenger's origin and destination (line 3), followed by selecting a grid where a micromobility vehicle is available for use. The algorithm checks chance constraint 3 on each grid $i \in N_{\text{micro}}$. For each request r, it first verifies if the passenger can use micromobility vehicles in grid i to reach their destination on time, then ensures that Constraint 3 holds (line 6), meaning the system can accommodate the request with sufficient confidence. If the fleet availability and time constraints are satisfied, the algorithm identifies an available vehicle, calculates the travel cost, and selects the vehicle with the minimum cost (line 7). The vehicle's status and location are updated accordingly. If the constraint is not satisfied (line 9), then grid i will not be suggested to request r.

Algorithm 1: Chance-Constrained Optimization for Trip Planning.

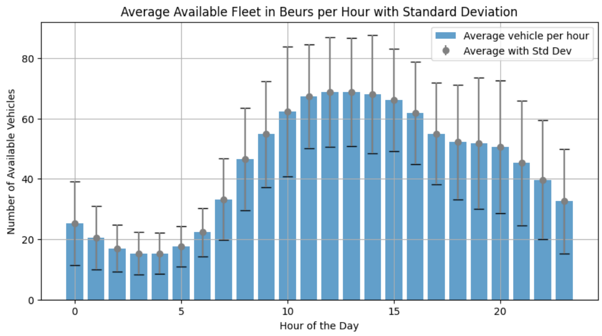
1 **Input:** N_{micro}, R^t; **Output:** Z^t_{micro} ; `// ` Z^t_{micro} `represents the obtained solution.`
2 **for** $r \in R^t$ **do**
3   Select public transport line based on r's origin and destination;
4   **for** $i \in N_{micro}$ **do**
5   **if** *passenger r can utilize micromobility vehicles within grid i to reach their destination on time* **then**
6   **if** *Constraint 3 is satisfied* **then**
7   choose vehicle k according to objective 1; update status of k;
8   **else**
9   continue;
10   **end**
11   **else**
12   continue;
13   **end**
14   **end**
15 **end**

3 Results

We utilize demand and supply data from a leading shared micromobility provider in Rotterdam, the Netherlands. The heatmap of pickup demand and parameters of fleet availability are shown in Figures 2a and 2b, respectively. We compare the proposed approach against two benchmarks: (1) an idealized model that assumes perfect knowledge of future demand and supply, and (2) a prediction model with noises. The performance metrics used for evaluation are as follows: False Positive—the count of cases where an alternative is recommended to passengers despite no micromobility vehicle being available; False Negative—the count of cases where no recommendation is made to passengers, even though a micromobility vehicle was available; and Served R (%)—the percentage of passengers who are not served due to incorrect recommendations. The results demonstrate that the proposed approach consistently yields significantly better selections while maintaining a high percentage of served passengers. In contrast, the prediction model with noise exhibits higher rates of False Negative and fluctuating served passenger rates, especially as the number of requests increases. This indicates that the proposed approach delivers reliable performance for passengers.



(a) *Heatmap of Pickup Demand*



(b) *Mean and Variability of Available Fleet Size*

Figure 2 – *Case study in Rotterdam City Center (Beurs)*

Table 1 – *Comparison of Approaches with Different Instance Sizes*

Instance Size		Proposed Approach			Idealized Model			Prediction Model with Noises		
K	R	False Positive	False Negative	Served R (%)	False Positive	False Negative	Served R (%)	False Positive	False Negative	Served R (%)
2	5	0	0	80	0	0	80	0	2	40
2	10	0	0	90	0	0	90	0	4	50
2	20	0	0	95	0	0	95	4	7	40
5	5	0	0	100	0	0	100	0	3	40
5	10	0	0	100	0	0	100	0	6	40
5	20	0	0	100	0	0	100	0	8	60
10	5	0	0	100	0	0	100	0	4	20
10	10	0	0	100	0	0	100	0	6	40
10	20	0	0	100	0	0	100	0	13	35

K: number of scooters; R: number of requests.

4 Discussion

The proposed stochastic optimization model presents a novel approach to addressing the uncertainty in shared micromobility demand and supply, a critical factor in urban multimodal transport systems. By accurately predicting demand distributions and estimating supply uncertainty at various locations, the model enables passengers to make more informed and reliable decisions about their trips. The use of stochastic approximation methods ensures that the recommendations are robust to the inherent variability of vehicle availability, ultimately reducing passenger frustration and improving the overall efficiency of transport networks. One of the key strengths of the model lies in its adaptability to different urban contexts, allowing for flexible integration with existing transport infrastructures. However, the success of this approach depends heavily on the availability of high-quality real-time data and the ability to continuously refine the predictive models based on changing conditions. Another limitation of our approach is the lack of consideration for demand adaptation in response to trip planning information, suggesting a need for a double-anticipatory or equilibrium model to better capture the dynamic interplay between demand adjustments and planning decisions. Future research could also explore the incorporation of dynamic pricing models, demand-side optimization, and the potential environmental benefits of optimizing multimodal trip planning, especially in reducing traffic congestion and carbon emissions.

References

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