Reliable Multimodal Trip Planning with Shared E-Micromobility under Battery and Behavioral Uncertainty

Sara Momen*[1], Yousef Maknoon[2], Bart van Arem[1], and Shadi Sharif Azadeh[1]

[1]Transport and Planning Department, Delft University of Technology, Netherlands
[2]Engineering, Systems and Services Department, Delft University of Technology, Netherlands

Short summary

Multimodal trip planners that combine public transport and shared e-micromobility face a fundamental reliability challenge: a vehicle that appears available at recommendation time may be unusable when the traveler arrives, due to battery depletion, competing demand, or individual range anxiety. This paper proposes a reliability-aware multimodal trip planning framework that embeds battery uncertainty and passenger behavioral heterogeneity directly into the recommendation problem. The model operates on a flow-based, time-expanded network and maximizes user welfare while conditioning micromobility transfers on predicted usability probabilities derived from Markovian fleet forecasts. Transfers or trips whose predicted success probability falls below an operator-defined threshold are excluded from the feasible set. The framework is evaluated on a multimodal network in Rotterdam through event-based simulation that separates planning-time beliefs from realized system conditions. The results reveal that introducing reliability thresholds reduces micromobility-leg failure rates from roughly 25% under myopic planning to below 5%, at the cost of about four additional minutes of walking. For longer trips, stricter thresholds reposition e-scooters as feeders to public transport rather than eliminating them.
Keywords: Multimodal trip planning, Shared electric micromobility, E-micromobility usability, Passenger behavior, Flow-based optimization

1 Introduction

Multimodal trip planning increasingly integrates shared micromobility as first- and last-mile connections to public transport (Li et al., 2024). In electrified fleets, vehicle availability and battery levels vary in real time, so a micromobility vehicle that appears present in the system may be unusable when the traveler arrives. These execution failures are a structural feature of electrified shared mobility, weakening the credibility of recommended trip chains.

Operational instability is compounded by the fact that micromobility feasibility is user-dependent. The presence of a vehicle does not ensure its acceptance and usability, since travelers differ in the minimum battery level they consider sufficient for their intended trip. Empirical evidence indicates that range anxiety toward shared electric vehicles varies substantially across individuals (Burghardt et al., 2025). As a result, the same predicted fleet condition may generate distinct feasible sets across users. Despite increasing attention to micromobility integration, multimodal trip planning models largely represent vehicle availability as a deterministic input and assume that a displayed vehicle remains usable at execution.

Existing literature in multimodal transportation spans operator-level design problems, fleet configuration, service network design (Posada et al., 2017; Azadeh et al., 2022), and user-level itinerary optimization that minimizes generalized cost or maximizes utility (Atasoy et al., 2015; Zhang et al., 2025). The uncertainty is considered through stochastic demand, travel time variability, or fixed-schedule public tranport disruptions (Mo et al., 2025; Ding et al., 2024). Therefore, the uncertain nature of usability of shared e-micromobility is overlooked in the multimodal tranportation literature. Models capturing the usability uncertainty focus primarily on fleet operations from the shared operator persective such as optimizing rebalancing and recharging plans(Zhou et al., 2023; Momen et al., n.d.), whereas user-facing trip planners assume that a displayed vehicle remains usable at execution.

This study introduces a user-dependent reliability metric for evaluating the shared e-micromobility leg of multimodal trips. When planning a trip, the availability of e-micromobility vehicles is in-

herently uncertain, and users exhibit varying preferences regarding acceptable battery levels. Consequently, an e-micromobility vehicle's *usability* is defined by its physical presence and its having sufficient battery level to meet a specific user's needs. To forecast near-future usability, vehicles are categorized into three battery-level classes: inactive, low-power, and high-power. While high-power vehicles can accommodate varying demands, low-power vehicles can serve trips of average length or shorter. A calibrated choice model is used as an exogenous input to simulate whether users battery dependent usage behavior. Within the trip-planning framework, e-micromobility zones are only considered "admissible" for a route search if their predicted usability exceeds an operator-defined reliability threshold. The system then evaluates the admissible options and recommends the multimodal trip that maximizes user welfare. This approach integrates rolling-horizon forecasts of zone-level vehicle counts segmented by battery class, into a flow-based, time-expanded optimization framework. By jointly accounting for stochastic vehicle supply and heterogeneous user acceptance, the model successfully identifies eligible micromobility legs. The proposed framework was evaluated using a case study of a shared e-scooter system integrated with an electric bus transit network in Rotterdam, the Netherlands.

2 Methodology

Problem setting

We consider a welfare maximization multimodal trip planner coordinating scheduled public transport (electric buses on fixed routes) with shared electric micromobility (geo-fenced e-scooters). Walking connects passengers to transit stops and micromobility pickup zones. Each passenger submits a trip request r defined by an origin o_r, destination d_r, and a time window $[a_r, b_r]$ specifying the earliest departure and latest acceptable arrival.
Battery charge is discretized into three categories $p \in \mathcal{P}\{n, l, h\}$, representing inactive, low-power, and high-power vehicles. Only low- and high-power vehicles are eligible for recommendation. For each zone and future time step, the planner receives predicted vehicle counts in each battery class from a Markovian forecast.
A shared mobility leg is defined as reliable if the predicted probability that at least one user-acceptable e-scooter is available at the designated pickup zone exceeds a reliability threshold Θ. Let $\rho_i^{r_t}$ denote the predicted usability probability of request r at zone i and arrival time t. For each request, pickup zones with $\rho_i^{r_t} < \Theta$ are excluded from the admissible set prior to optimization. Passengers are classified as range-anxious if the utility of declining micromobility exceeds that of selecting a low-power vehicle, based on a calibrated discrete choice model (Burghardt et al., 2025). Range-anxious passengers require at least one high-power vehicle; flexible passengers accept either class.

Flow-based time-expanded optimization model

The multimodal network is represented as a directed graph $G = (\mathcal{N}, \mathcal{A})$ composed of three interconnected layers. The walking layer $\mathcal{N}^{\text{walk}}$ contains static nodes for each physical location. The micromobility layer $\mathcal{N}^{\text{micro}}$ represents geo-fenced zones. The public transport layer $\mathcal{N}^{PT}$ is time-expanded, where each node (i, k) corresponds to the scheduled arrival or departure of bus trip $k \in \mathcal{K}^{PT}$ at stop i. After the reliability filter removes infeasible rental arcs, the resulting graph is deterministic, defining the feasible search space.
For each request r, the planner maximizes deterministic user welfare based on passenger valuation of travel time and monetary cost across multimodal trip alternatives. Let binary variable x_{uv}^r indicate whether request r uses arc (u, v), g_r indicate multimodality, and z_r^m indicate whether mode m is used. The objective function aggregates arc-level travel times and costs along the

selected path:

$$
\begin{aligned}
V_r = & \sum_{m \in \mathcal{M}} ASC^m \cdot z_r^m + \sum_{(u,v) \in \mathcal{A}^{walk}} x_{uv}^r \beta_r^{\text{walk}} \tau_{uv} \\
& + g_r \Bigg(\sum_{(u,v) \in \mathcal{A}^{PT}} x_{uv}^r \left(\beta_r^{\text{mainTime}} \tau_{uv} + \beta_r^{\text{PTwait}} w_u^r + \beta_r^{\text{mainCost}} c_{uv} \right) \\
& \quad + \sum_{(u,v) \in \mathcal{A}^{micro}} x_{uv}^r \left(\beta_r^{\text{subTime}} \tau_{uv} + \beta_r^{\text{subCost}} c_{uv} \right) \Bigg) \\
& + (1 - g_r) \Bigg(\sum_{(u,v) \in \mathcal{A}^{micro}} x_{uv}^r \left(\beta_r^{\text{mainTime}} \tau_{uv} + \beta_r^{\text{mainCost}} c_{uv} \right) \Bigg),
\end{aligned}
\tag{1}
$$

where where ASC^m captures intrinsic mode preferences, $\beta^{mainTime}$, $\beta^{mainCost}$, $\beta^{subTime}$, and $\beta^{subCost}$ denote the time and cost sensitivity coefficients for main and sub modes of transport, respectively. τ_{uv} denotes travel time and cost parameters are mode-specific. Parameter values are adopted from Montes et al. (2023) for a homogeneous population. Only the deterministic component of utility enters the optimization problem.

As a pre-processing step, micromobility rental arcs that fail to meet the reliability criterion are removed from the search space. The definition of usability depends on passenger classification. For *range-anxious* passengers, ρ_i^{rt} denotes the probability that at least one high-power vehicle will be available at the expected arrival time. For *flexible* passengers, it denotes the probability that at least one usable vehicle, either low- or high-power, will be available. These probabilities are derived from the exogenous Markovian forecast of zone-level battery-class counts. Formally, the admissible arc set for request r_t is

$$
\mathcal{A}^{r_t} = \mathcal{A} \setminus \left\{ (u,v) \in \mathcal{A}^{\text{rent}} : \; v = (i, \text{micro}), \; \rho_i^{rt} < \Theta \right\}. \tag{2}
$$

The threshold Θ operates on the belief state and defines feasibility at planning time. Realized service level, by contrast, is measured ex post and reflects the stochastic evolution of the physical system. The filter therefore reduces but does not eliminate execution risk.

The optimization is subject to flow conservation ensuring a connected path from origin to destination:

$$
\sum_{v \in \mathcal{N}} x_{uv}^r - \sum_{v \in \mathcal{N}} x_{vu}^r = \begin{cases} 1 & \text{if } u = o_r \\ -1 & \text{if } u = d_r \\ 0 & \text{otherwise} \end{cases} \qquad \forall u \in \mathcal{N} \tag{3}
$$

Mode activation links arc usage to binary mode indicators, and multimodality is detected when both public transport and micromobility are active:

$$
g_r \geq z_r^{PT} + z_r^{\text{micro}} - 1 \tag{4}
$$

$$
g_r \leq z_r^{PT} \tag{5}
$$

$$
g_r \leq z_r^{\text{micro}} \tag{6}
$$

Public transport scheduling constraints enforce timetable consistency. For boarding arcs (u, v) with $v = (i, k)$, the passenger's arrival time plus waiting time must equal the scheduled departure $td_{i,k}$:

$$
t_u^r + w_u^r \geq td_{i,k} - M(1 - x_{uv}^r) \tag{7}
$$

$$
t_u^r + w_u^r \leq td_{i,k} + M(1 - x_{uv}^r) \tag{8}
$$

where t_u^r denotes the arrival time of request r at node u, w_u^r the waiting time, and M a sufficiently large constant. Time continuity for all alighting arcs ensures $t_v^r \geq t_u^r + \tau_{uv} - M(1 - x_{uv}^r)$, and trip request time windows constrain $t_{o_r}^r \geq a_r$ and $t_{d_r}^r \leq b_r$.

Rolling-horizon framework

The model is implemented in a sequential rolling-horizon framework. Upon assignment of an itinerary to request r_t, the belief state of the e-scooter fleet is adjusted to reflect the planned trip. The Markovian prediction model is reinitialized from this revised inventory, and usability probabilities are recomputed before processing the next request. Previously assigned itineraries remain

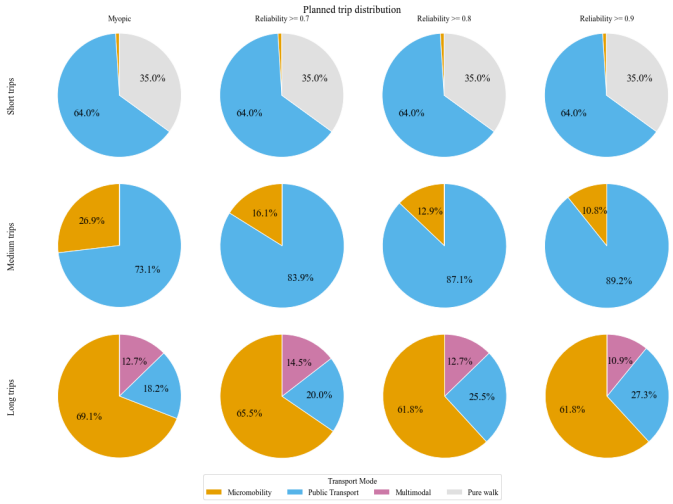


Figure 1: Planned trip distribution across different reliability scenarios

fixed. This structure captures the endogenous interaction between successive trip assignments and shared resource availability while preserving computational tractability.
We evaluate the performance of service level in terms of success of recommended trip by simulating the proportion of recommended legs successfully executed upon arrival. Because fleet conditions evolve stochastically and users compete for vehicles, zones satisfying $\rho_i^{rt} \geq \Theta$ at planning time may still fail at realization. The filter therefore reduces but does not eliminate execution risk.

3 Results and discussion

Experimental setup

Experiments are conducted on an urban network centered on Rotterdam Centraal, combining scheduled bus services (1,190 active schedules from GTFS data) and dockless shared e-scooter operations across geo-fenced zones. Passenger demand is synthetically generated across three urban trip-length categories based on shortest path walking time between origin and destination, i.e., short (<30 min), medium (30–60 min), and long (>60 min). We generate 100 origin-destination pairs per category. Arrivals follow a time-dependent Poisson process. Performance is evaluated under four reliability thresholds: Myopic ($\Theta = 0$) which assumes full usability in geo-fenced areas, and $\Theta \in \{0.7, 0.8, 0.9\}$. An event-based simulation separates planning-time beliefs from execution-time realizations.

Impact on planned trip composition

Figure 1 illustrates how reliability thresholds alter the composition of planned itineraries across trip lengths. The impact of reliability control is strongly dependent on trip characteristics. For short trips, mode shares remain largely stable across thresholds. Bus dominates, while approximately 35% of trips are completed by pure walking and only about 1% involve shared e-micromobility as the primary mode. Because micromobility offers limited spatial advantage over walking at short distances, restricting its usability has negligible influence on optimal plans.
For medium trips, micromobility accounts for a meaningful share of standalone itineraries under the *Myopic* scenario. As the reliability threshold increases from to 90%, this share declines steadily, with demand shifting toward scheduled public transport. The reduction in micromobility-only trips indicates that reliability filtering effectively eliminates itineraries predicated on moderately risky scooter availability, shifting passengers toward more predictable, single-mode transit and highlighting a distinct aversion to multimodality for medium-length urban trips. For long urban trips, although stricter thresholds change micromobility-only itineraries, micromobility-only trips remains the most selected mode. The decrease in micromobility as the main mode is not completely shifted to public transport and it remains present in a substantial share of multimodal chains as a first- and last-mile connector. Reliability control thus restructures the functional role of micromobility rather than uniformly suppressing its usage.

Impact on user welfare

As the threshold increases from the Myopic case to $\Theta = 0.9$, the user welfare changes as shown in Table 1; average total travel time rises and walking time increases from 3.5 to 7.5 minutes. Despite increased total travel time, average trip cost decreases by 14% as itineraries shift toward fixed-fare public transport.

Table 1: Trade-off between estimated utility and realized service level for trips with e-micromobility legs.

Scenario	**Est. utility**	**Service level (%)**	**Avg. walk (min)**	**Avg. cost (€)**
Myopic	−1.65	75.5	3.5	4.16
$\Theta \geq 0.7$	−1.77	91.7	5.9	3.87
$\Theta \geq 0.8$	−1.79	95.0	6.7	3.74
$\Theta \geq 0.9$	−1.83	97.6	7.5	3.57

Table 1 summarizes the reliability–utility trade-off. The Myopic scenario yields the highest utility but nearly 25% of micromobility-including trips fail at execution. A threshold of 80% reduces the failure rate to 5%, capturing most of the attainable reliability improvement. Raising the threshold from 80% to 90% yields only an additional 2.6 percentage-point gain in service level but entails a reduction in utility and will limit the admissible set for searching trip options even more, exhibiting diminishing returns to increasingly conservative reliability control. A threshold around 80% achieves a substantial improvement in execution success while retaining sufficient flexibility for the optimizer to identify high-utility multimodal alternatives.

Managerial implications

The results reveal a structural shift in the role of shared micromobility while considering their reliability uncertainty in a multimodal trip plannig problem. For long urban trips, reliability thresholds do not eliminate micromobility from optimal itineraries but reallocate its function toward first- and last-mile connectivity near major transit stops. The reliability threshold emerges as a design parameter governing the trade-off between execution stability and solution flexibility. The effectiveness of the approach depends on accurate short-term predictions of battery states and vehicle distribution; when such information is limited, planning outcomes converge toward myopic performance which can have substantial failure rate.

4 Conclusions

This paper proposed a reliability-aware multimodal trip planning framework that integrates scheduled public transport (e-bus) and shared e-micromobility while accounting for stochastic e-micromobility availability, battery charge evolution, and heterogeneity in users' behavior toward battery-acceptance. By conditioning the admissible search space on battery-conditioned usability probabilities of shared e-micromobility, the model reduces ghost-trip recommendations without eliminating micromobility where it enhances network connectivity.

The results demonstrate that reliability control reshapes rather than suppresses micromobility usage. Moderate thresholds capture most attainable reliability gains while preserving welfare-oriented trip options. Future research could extend the approach to multi-operator settings, incorporate richer behavioral segmentation, or evaluate the framework under operational deployment conditions.

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