A scalable link-based electric Mobility-as-a-Service assignment game model with charging activity

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INTRODUCTION

The concept of Mobility-as-a-Service (MaaS) has gained significant attention in recent years, driven by the emergence of new mobility options such as ride-hailing and micromobility services. MaaS platforms offer travelers a variety of integrated mobility solutions, bundling different modes of transport into cohesive trip options. These bundles enable travelers to select optimal routes across a multimodal network based on their individual preferences. Simultaneously, service operators in the MaaS system make resource allocation decisions, such as determining pricing strategies and service capacities. Achieving equilibrium between these decisions presents a complex challenge. The growing adoption of electric vehicles further complicates this by introducing the need to integrate vehicle charging behaviors, which often involves matching service operators with energy providers.

Previous studies (Liu and Chow, 2023; Yao and Zhang, 2024) employ a many-to-many stable matching framework to model the joint decision-making of travelers and operators within a MaaS system. This framework formulates a bilevel problem: the lower level addresses multimodal flow assignments, while the upper level focuses on pricing strategies. Decision variables are applied at the link level, with nonlinear functions modeling congestion effects on access links (Liu and Chow, 2023; Yao and Zhang, 2024) and travel links (Yao and Zhang, 2024). Both studies assess the stability of the joint assignment by applying the user equilibrium (UE) condition for active paths between origin-destination (OD) pairs, accounting for both travel time and cost. To resolve potential instabilities, minimum subsidies are introduced to ensure stable outcomes. If instabilities arise under the existing pricing scheme, subsidies are allocated to enforce stability conditions.

The link-based MaaS assignment models currently available rely on complex algorithms to address equilibrium conditions, limiting their scalability to larger networks. Rather than using UE conditions to assess stability, Liu et al. (2024) propose a bilevel model that adopts a stochastic assignment framework similar to the stochastic user equilibrium (SUE) problem, thereby bypassing the need for complementary condition checks. At the flow assignment level, decision variables from both travelers and operators form a coalition within a path-level joint utility objective, while the upper level focuses on determining operators' pricing strategies, forming a Stackelberg game. Though this model is less computationally demanding, the required path enumeration process remains a scalability challenge.

More scalable approaches are needed to not only facilitate real-world MaaS applications but also accommodate the integration of charging decisions required in electric MaaS (eMaaS) systems. In an eMaaS system, matching between operators and energy providers is incorporated, alongside traveler-operator matching. This adds charging facility-related nodes and links to the multimodal network. In this market setting, charging costs are influenced by station capacities and the access link costs to charging stations. These costs can either be borne by eMaaS users or offset through subsidies. The transfer of costs from the operator-charging side to the traveler-operator side increases the complexity of the model, and no existing framework adequately addresses these three-sided decisions in a scalable manner.

We propose a Perturbed Utility Route Choice (PURC) based framework (Fosgerau et al., 2022) to model the three-sided eMaaS system design problem. The PURC approach applies the concept of a random utility model (RUM) to link-level properties, assuming additive path utilities. In this framework, we assume store-and-forward links with service queues, meaning that link flow remains uncongested until capacity is reached. Once capacity is exceeded, excess flows are diverted to other uncongested links. This structure simplifies previous link-based models by using stochastic assignment while avoiding path enumeration, significantly improving scalability. This framework enables the incorporation of the energy provider side in large-scale eMaaS networks.

METHODOLOGY

We model the eMaaS system as a Stackelberg game in a bilevel structure using an interval-based approach. We divide a typical timeframe (e.g., 24 hours) into multiple intervals, each characterized by a unique, known OD demand pattern. Each interval represents a steady-state flow assignment problem for the traveler-operator matching process, while the charging operations occur between intervals, representing an operator-energy provider matching problem. The two matching problems forms the lower-level problem. The upper-level maximizes the operators' profit based on the lower-level output. We introduce lower problems separately, then present the overall problem at the end.

2.1. Traveler-operator matching problem

The mobility services considered include mass transit (MT) and mobility on demand (MOD) services. The multimodal network, denoted by (N_M, A_M), consists of service nodes and links, with access and egress links connecting MOD and MT nodes. M represents the set of operators. MT links are pre-existing and have fixed prices, travel times, and capacities. In contrast, MOD operators determine the capacities of their nodes and their link prices, and all nodes owned by the same operator are fully connected. The total capacity of all MOD links originating from a given node is equal to the capacity of that MOD node.

To formulate the matching problem, we adopt the Perturbed Utility Route Choice (PURC) model (Fosgerau et al., 2022) to formulate an assignment model. For each origin-destination (OD) pair, the total utility experienced by each traveler consists of two components: link utility and perturbed utility, formulated as:

$$\min U(\boldsymbol{x}) = l^{\intercal}(\boldsymbol{u} \circ \boldsymbol{x}) + l^{\intercal} F(\boldsymbol{x}) \tag{1}$$

The flow conservation constraints require that the sum of flows $\boldsymbol{x}$ at each node equals: -1 if it is an origin node, 1 if it is a destination node, and 0 otherwise. The perturbed utility term must be a convex function, with $F(0) = F'(0) = 0$. In this study, we use $F(x) = x^2$ as suggested in one of the alternatives in Fosgerau et al. (2022).

The lower-level model jointly determines traveler flows and hub capacities. Therefore, we formulate the lower-level objective as the weighted sum of traveler utility and hub cost:

$$T\colon \min \Phi_1 = U(\boldsymbol{x}) + \alpha \sum_{n \in N_{MOD}} v_n z_n \tag{2a}$$

The capacity variables z_n denote the fraction of the maximum allowable capacity v_n for hub MOD nodes. The weight coefficient α modulates the impact of hub costs on the overall objective; in practice, α is chosen to be sufficiently small so that the lower-level problem remains driven by the PURC-based flow assignment. For interval i, T_i is a quadratic programming (QP) model, solvable on a large scale using off-the-shelf solvers.

2.2. Operator-energy provider matching problem

A charging dedicated network (N_C, A_C) consists of MOD nodes and charging station nodes, assuming that charging activities are only part of MOD operators' decisions. The charging demand for each operator corresponds to the capacity solution from the traveler-operator problem in the previous interval. The macroscopic charging demand can be captured by dispersion models which can be calibrated using real-world charging data. Additionally, rebalancing is incorporated to reflect the MOD fleet movement, corresponding to demand shifts in the following interval. This aligns with real-world practices where recharging activities are often integrated with rebalancing flows for greater efficiency.

Similar to its counterpart, the operator-energy provider matching problem (G_i) between interval i and $i+1$ is formulated by minimizing the total operator disutility $U_{s'}(x_{s'r'})$ for all rebalancing pairs $s' \in S'_{i,i+1}$ and links $r' \in A_C$. The total recharge flow must meet the charging demand for each MOD operator in each interval. Recharging and rebalancing flows are jointly determined, along with capacity decisions at each charging node by the energy providers. The combined recharging and rebalancing flow equal to the shift in node capacities for each time propagation. The stand alone G_i is also formulated as a QP.

2.3. Three-sided market Stackelberg game

We formulate the whole three-sided market as a Stackelberg game: the MOD operator and energy provider leads by setting service and charging prices, and travelers and operators follow by selecting their most desirable paths within the multimodal network while operators and energy providers adjust hub capacities accordingly. Flows and hub capacities are determined within the lower-level assignment game, while the upper level sets the prices for these added services. The charging demand in G_i is dependent on the operator capacities determined in T_i, while the rebalancing flow for G_i is jointly determined by the fleet sizes obtained from solving T_i and T_{i+1}. Thus, the lower-level eMaaS problem $L_{i,i+1}^{low}$ is solved by jointly addressing T_i, G_i, and T_{i+1}. The pricing schemes for both operators and energy providers are formulated on the upper-level $L_{i,i+1}^{up}$ by maximizing the system profit. Costs from both operators and energy providers are transferred to travelers via service prices, which is captured by the upper-level problem. The eMaaS problem for the entire day, denoted as L_I (where I is the set of all intervals), is solved in a cyclic manner, as the operator-energy provider matching problem in the last interval is influenced by the start of the following day.

L_I is formulated as a multi-leader multi-follower game (MLMFG). Due to the complex interactions among intervals and price transfers, we propose an iterative algorithm. For each service interval i, the stand-alone bilevel problem L_i is first solved without considering the charging related cost. By reformulating L_i into a single-level problem via the Karush–Kuhn–Tucker (KKT) conditions of T_i, L_i can be solved to optimality. Subsequently, the bilevel problem only considering charging and rebalancing is solved in a similar manner after obtaining MOD node capacities and service prices. The obtained charging cost is then fixed and incorporated into the upper-level cost. We iteratively update the service and charging related cost and capacities until the upper-level objective of L_I converges, yielding the final solution for L_I. Between iterations, proper update mechanism using the concept of alternating direction method of multipliers (ADMM) (Xi et al. 2024) is developed to ensure convergence.

NUMERICAL EXAMPLE

We use a toy network to illustrate the model framework. Fig. 1 shows the service-specific network. The solid lines connecting nodes 1, 2, and 3 represent existing transit links, while the dotted black lines indicate links outside the MaaS system. The network expands with the introduction of MOD services by adding MOD-specific nodes and corresponding access and egress links. Two intervals are studied. In interval 1, the OD demand is 500 from node 0 to node 3 and 300 from node 3 to node 0, with maximum MOD capacities of 500, 300, and 200 at nodes 0', 2', and 3', respectively. In interval 2, demand changes to 200 from node 0 to 3, and 600 from node 3 to 0. The traveler value of time (VOT) is \$20/hour.

Fig 2 illustrates the recharging network. There are two charging nodes available, with only MOD fleets requiring recharging. The time cost is considered for both charging and rebalancing intervals. The MOD operator's VOT is also $20/hour. For simplicity, we assume 30% of the MOD fleet from interval 1 requires recharging. A full reset of the state of charge (SOC) occurs by the end of interval 2 (e.g., centralized overnight slow-charging), isolating the intervals from each other. We solve the three-interval system using a single-level structure in Gurobi 11.0.3. Fig 1(a) and 1(b) show the results of the two service intervals, while Fig 2 illustrates the rebalancing and recharge flows between intervals at the path level.

The charging and rebalancing flows in Fig 2 result from the capacity decisions made in intervals 1 and 2. Since the total capacity required in interval 2 exceeds that in interval 1, additional resources are needed, leading to the creation of a dummy node (3*) as shown in Fig 2

We also applied the bilevel problem of a single service interval to Sioux-Falls network with 29 OD pairs. The reformulated single-level problem is solved to optimality under 10 minutes. In contrast, previous studies at a similar scale requires hours to solve (Liu and Chow, 2024; Yao and Zhang, 2024). The reduced computational complexity shows its potential in larger scale applications.

COMPUTATIONAL EXPERIMENTS

A comprehensive experiment will be presented, including:

- A test network based on a multimodal and charging network in part of New York City.
- A multi-interval system that considers the cyclic nature of demand patterns.
- Incorporating heterogeneous travelers, classified by OD pairs and population groups.
- Splitting charging facilities into different types to reflect heterogeneous charging decisions.

The proposed framework can significantly scale the evaluation of MaaS systems, especially with the addition of charging activities. This will provide valuable insights for policymakers and platform designers, enhancing the understanding of real-world eMaaS applications.

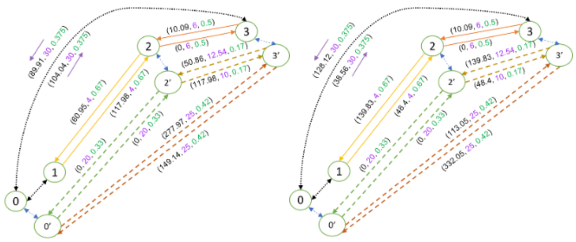
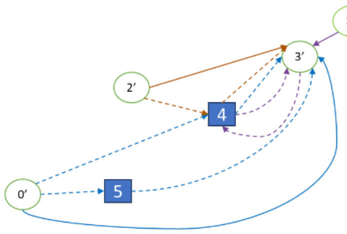


Figure 1. Service network and results of (a) service interval 1 and (b) service interval 2; elements included in the brackets are (flow, price, time).



Path	Flow	Time
(0', 3', 0*)	79.09	0.42
(0', 4, 3', 0*)	42.92	0.5
(0', 5, 3', 0*)	42.92	0.5
(2', 3', 2*)	34.19	0.17
(2', 4, 3', 2*)	35.40	0.25
(3', 4, 3'', 3*)	60	0.17
(3*, 3')	37.36	0

Figure 2. Recharge network and flow for recharging and rebalancing

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