Large-Scale Multimodal Transit Package Optimization: The Case of Hong Kong

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SHORT SUMMARY

Mobility-as-a-Service (MaaS) allows travelers to access multiple mobility services through an integrated platform providing a seamless multimodal transport system. In this paper, we evaluate the financial feasibility of mobility packages for the city of Hong Kong. We formulate a revenue and social welfare maximization problem with a specific focus on transit packages. We incorporate demand elasticity in the modeling framework and capture the changes in travel demand, transport system travel time, social welfare and transit service operators' profitability caused by the implementation of transit package in an activity-based traffic model. A gradient-based optimization framework is developed to solve the proposed optimization problems. Numerical experiments on the multimodal network of Hong Kong Island for both government and commercially owned transit packages indicate that transit package implementation can reduce total system travel time and increase social welfare. Moreover, transit package can induce travelers to reduce auto trips and increase transit trips.

Keywords: Transit package; Iterative Backpropagation; Activity-based modeling; Gradient-based optimization

1. INTRODUCTION

Transport networks and services have been enjoying constructive transformation in recent years along with the development of smart technologies. The uptake of peer-to-peer markets and smartphone applications have enabled transport service providers to satisfy customers' diverse travel needs with multimodal mobility solutions that are consumed as a service. This new direction has become known as Mobility-as-a-Service (MaaS). The potential benefits of MaaS are promising. For car-centric societies, MaaS can potentially reduce people's reliance on car. For public-transport-oriented societies, MaaS is claimed to offer a way to achieve higher mobility efficiency and fuller utilization of each public transport mode with each mode not losing out in revenue, that is, win-win between public and private transport service providers (TSPs). However, as an emerging mobility solution, the actual impact of MaaS and whether this new business model is economically viable are still unclear and may be manifold.

Currently, MaaS is realized through bundling several transport modes into a single platform. MaaS platform operator acts as a mobility broker, coordinating with multiple TSPs, create mobility packages, and sell packages to travelers. Travelers who choose to buy a MaaS package can access a wide range of modes (e.g., bus, rail, ferry, taxi, etc.) using a single account and pay only once for daily, weekly, or monthly travel. This combined payment feature is not just the simple summation of fares of individual trip legs but opens up to great opportunities of pricing. MaaS platform operator can achieve its own objective by strategically pricing mobility packages.

Reviewing existing studies on MaaS, most researchers attempted to discuss business opportunities of MaaS qualitatively and explore individual traveler's attitudes towards this new mobility scheme. Hirschhorn et al. (2019); Smith et al. (2020); Smith and Hensher (2020) and Wong et al. (2020) qualitatively analyzed potential business models for MaaS. They mainly pointed out that the role of a MaaS platform operator is like a mobility service broker, but who plays the role of broker determines whether the long-term goal is societal-driven or commercial-driven. Alonso-González et al. (2020); Caiati et al. (2020) and Vij et al. (2020) designed stated preference surveys and developed discrete choice models to characterize travelers' demand for this new service. In recent studies on the MaaS Sydney trial, Hensher et al. (2021) and Ho et al. (2021) claimed that financial viability could hardly be proven in MaaS business models. They highlighted that public transport is the backbone of a MaaS platform which is heavily subsided. As a result, subsidy is necessary to ensure the sustainability of MaaS business models. In this study, we plan to analyze and optimize for optional transit MaaS bundles under subsidized and unsubsidized business models for large-scale multimodal networks.

Solving mobility resource allocation and pricing problem in a MaaS platform generates a multimodal transit optimization problem. Recent studies by Pantelidis et al. (2020), Rasulkhani and Chow (2019), and Ma et al. (2021) took the initial attempts to analytically model a government-contracted MaaS platform by deriving a joint equilibrium for both traveler and operator side decision process. In the transit optimization literature, however, operator decisions are commonly formulated as a Stackelberg game with the bi-level formulation structure which requires solving the assignment equilibrium at the lower level for every iteration of the optimization with respect to the upper-level decision, increasing the overall intractability of the problem. Therefore, past studies of transit optimization mainly analyzed the problems on a single transit line or without underlying route flow distribution or modal interaction to increase the tractability of the upper-level optimization problem (Sun et al., 2019; Tang et al., 2017; Wang and Deng, 2019; Yang and Tang, 2018). In addition, some studies were performed at a smaller scale or in reduced traffic dynamics due to computation complexity (Cavadas and Antunes, 2019; de Palma et al., 2015; Huang et al., 2016; Kaddoura et al., 2015; Li et al., 2016a; Liu et al., 2019; Lo et al., 2002; 2004). Kamel et al. (2020) applied GA in cluster computing setup for transit pricing optimization in a large-scale scenario. However, the study ignored demand elasticity due to the pricing change in the transit network.

Deploying mobility packages will change travelers' travel costs, which will affect their travel demand, activity pattern, route and mode choice, and place the resulting impacts on travelers' utility, transport system travel time, and operators' profitability. Therefore, a modeling framework that can account for the above-mentioned variations is necessary. Optimization of such model in large-scale setting is already an intractable task and require development of efficient algorithms. To this end, this study first develops a versatile formulation for transit operator profit and social welfare maximization problem in section 2. Furthermore, an efficient gradient based optimization algorithm is developed for large-scale implementation in section 3. Finally, a subsidized govt owned all-transit package scenario is analyzed in the context of optional mobility packages for the large-scale multimodal network of Hong Kong Island using real data. The results are presented in section 4. Finally, section 5 concludes the paper.

2. Problem Formulation

We account for two different types of package operators in our formulations: commercial and government operators. A commercial operator is driven by profit whereas a government operator aims to maximize the overall social welfare. In both cases, the revenue of package operation plays a critical role. System performance, on the other hand, determines the social welfare and is only of importance to a government authority while operating packages. To improve social welfare, the government operator can subsidize the system.

Consider a set of transit packages $m \in M$ are run by package operator $o_m \in O$ with package subscription cost c_m. A transit package contains a set of fare links $fl \in FL$. A fare link is a transit leg of a trip where the fare becomes due. A person who buys a package enjoys the discounted fare $\lambda_{m,\phi_{fl}} \times fr_{fl}$ for the fare links that belong to that package, where ϕ_{fl} is the fare link discount set that fl belongs to. However, the package cost c_m has to be paid upfront. $\lambda_{m,\phi}$ are discount factors for fare link set ϕ in package m. fr_{fl} is the original fare of the fare link fl.

Each fare link fl is owned by an operator $o_{fl} \in O$. The fare link operator receives the discounted fares from the passengers and reimbursement for a fraction of the discounts by the package operator. This fraction is termed the reimbursement ratio $\lambda_{m,o}$, negotiated between the package operator and the fare link operator for each package. We assume that the passengers without any package subscription are also subscribed to a package with zero discounted fare and zero package price. This allows us to formulate a common revenue function for all operators irrespective of them operating packages, operating fare links or both.

In this system, the revenue earned by operator $o \in O$ can be expressed as equation (1).

$$\begin{aligned} J_o = & -\sum_{m\in M_o}\sum_{\phi\in\Phi_m}\sum_{fl\in FL_\phi} n_{m,fl}\times fr_{fl}\times\lambda_{m,\phi}\times\lambda_{m,o_{fl}} \\ & +\sum_{m\in M}\sum_{\phi\in\Phi_m}\sum_{fl\in FL_{\phi,o}} n_{m,fl}\times fr_{fl}\times\left\{1-(1-\lambda_{m,o})\times\lambda_{m,\phi}\right\} \\ & +\sum_{m\in M_o} n_m\times c_m \end{aligned} \tag{1}$$

where $n_{m,fl}$ denotes the number of travelers using fare link fl while subscribing to package m and n_m denotes the number of travelers subscribed to package m. The operator's revenue optimization problem can be formulated in equation (2).

$$\begin{aligned} & \max_{c_m,\lambda_{m,o'},\lambda_{m,\phi}} J_o;\ \forall m\in M_o, o'\in O_{m,fl}, \phi\in\Phi_m \\ & s.t.,\ J_{o'}-\overline{J_{o'}}=0; \forall o'\in O_o \\ & \qquad c_m\in[c_m^{min}, c_m^{max}] \\ & \qquad \lambda_{m,o'}\in[0,1] \\ & \qquad \lambda_{m,\phi}\in[0.5,1] \end{aligned} \tag{2}$$

where the first constraint ensures that the participating fare link operators does not take loss by participating in the transit package.

As we use multinomial logit (MNL) model as the underlying choice model, social welfare is measured by optimizing the total expected maximum utility (EM Utility), which can be expressed as equation (3).

$$J_U = \frac{1}{\kappa\beta_{money}}\sum_{\eta\in N}\log\left(\sum_{\rho\in P_\eta}\exp(\kappa U_\rho)\right) \tag{3}$$

where $\eta \in N$ denotes a traveler and ρ denotes a plan. A plan encodes the choices that a traveler makes throughout the day. A plan includes a list of activities and trips and corresponding trip modes, departure times and routes. It also encodes the package subscription decision of the traveler. Each traveler chooses from a set of plans. The plan set is generated using MATSim. U_ρ denotes the utility of plan ρ. κ is the scaling parameter of the MNL model.

As expressed earlier, a government authority operating a package will try to maximize the social welfare at minimal cost. Hence, the objective for a government authority can be expressed as equation (4) subjected to the following constraints.

$$\begin{aligned} \max_{c_m,\lambda_{m,o'},\lambda_{m,\phi}} \quad & J_{Govt} + J_U \ ; \ \forall m \in M_o, o' \in O_{m,fl}, \phi \in \Phi_m \\ s.t., \quad & J_{o'} - \overline{J_{o'}} = 0; \ \ \forall o' \in O_{Govt} \\ & J_{Govt} \le 0 \\ & c_m \in [c_m^{min}, c_m^{max}] \\ & \lambda_{m,o'} \in [0,1] \\ & \lambda_{m,\phi} \in [0.5,1] \end{aligned} \tag{4}$$

In our experiments, we have included two types of decision variables, the package cost c_m and the reimbursement ratio $\lambda_{m,o}$.

3. Optimization Framework

The objective functions in both equations (2) and (4) are well defined within the bounds of decision variables even when the constraints are not satisfied. Hence, we can add the constraints as a penalty function in the objective and solve the problems as an unconstrained maximization problem. In this paper, we use gradient based algorithm ADAM (Kingma and Ba, 2015) for solving the optimization problem. We now derive the gradients of the revenue objective J_o and the EM utility J_U as follow.

$$\begin{aligned} \frac{\partial J_o}{\partial c_{m'}} = & -\sum_{m\in M_o}\sum_{\phi\in\Phi_m}\sum_{fl\in FL_\phi} \frac{\partial n_{m,fl}}{\partial c_{m'}} \times fr_{fl} \times \lambda_{m,\phi} \times \lambda_{m,o_{fl}} \\ & + \sum_{m\in M}\sum_{\phi\in\Phi_m}\sum_{fl\in FL_\phi} \frac{\partial n_{m,fl}}{\partial c_{m'}} \times fr_{fl} \times \left\{1-(1-\lambda_{m,o}) \times \lambda_{m,\phi}\right\} \\ & + n_{m'} \times \delta_{o,o_{m'}} + \sum_{m\in M_o} c_m \times \frac{\partial n_m}{\partial c_{m'}} \end{aligned} \tag{5}$$

$$\begin{aligned} \frac{\partial J_o}{\partial \lambda_{m',o'}} = & -\sum_{\phi\in\Phi_{m'}}\sum_{fl\in FL_\phi} n_{m',fl} \times fr_{fl} \times \lambda_{m',\phi} \times \delta_{o,o_{m'}} \times \delta_{o_{fl},o'} \\ & + \sum_{\phi\in\Phi_{m'}}\sum_{fl\in FL_\phi} n_{m',fl} \times fr_{fl} \times \lambda_{m',\phi} \times \delta_{o,o'} \times \delta_{o_{fl},o'} \end{aligned} \tag{6}$$

$$
\begin{aligned}
\frac{\partial J_U}{\partial \psi} &= \frac{1}{\kappa \beta_{money}} \sum_{\eta \in N} \frac{\kappa \sum_{\rho \in P_\eta} \exp(\kappa U_\rho) \times \frac{\partial U_{\rho,\eta}}{\partial \psi}}{\sum_{\rho \in P_\eta} \exp(\kappa U_\rho)} \\
&= \frac{1}{\beta_{money}} \sum_{\eta \in N} \sum_{\rho \in P_\eta} \left(Pr_{\rho,\eta} \times \frac{\partial U_{\rho,\eta}}{\partial \psi} \right)
\end{aligned}
\tag{7}
$$

where Ψ is used for both variables c_m and $\lambda_{m,o}$. $\delta_{o,o'}$ is the binary variable taking the value 1 if o and o' are same operators, 0 otherwise. Equations (5)-(7) are functions of link flow, travel time, package usage, utility, and choice probability gradients, which are the gradient of the equilibrium outputs of the underlying traffic assignment model. We derive these gradients using iterative backpropagation (IB) algorithm proposed by Patwary et al., (2021). As the underlying model, we used an activity based multi-modal traffic assignment model which is an extension of (Patwary et al., 2021a).

4. Numerical Experiments

In this study, we perform experiments for the large-scale multimodal network of Hong Kong Island (HKI) (Figure 1) using real data (Lee et al., 2017) at a 10% scale. The plan set is extracted beforehand from two MATSim scenarios with and without applying transit packages. An activity insertion strategy was implemented while generating the plans to account for the effect of elastic demand.

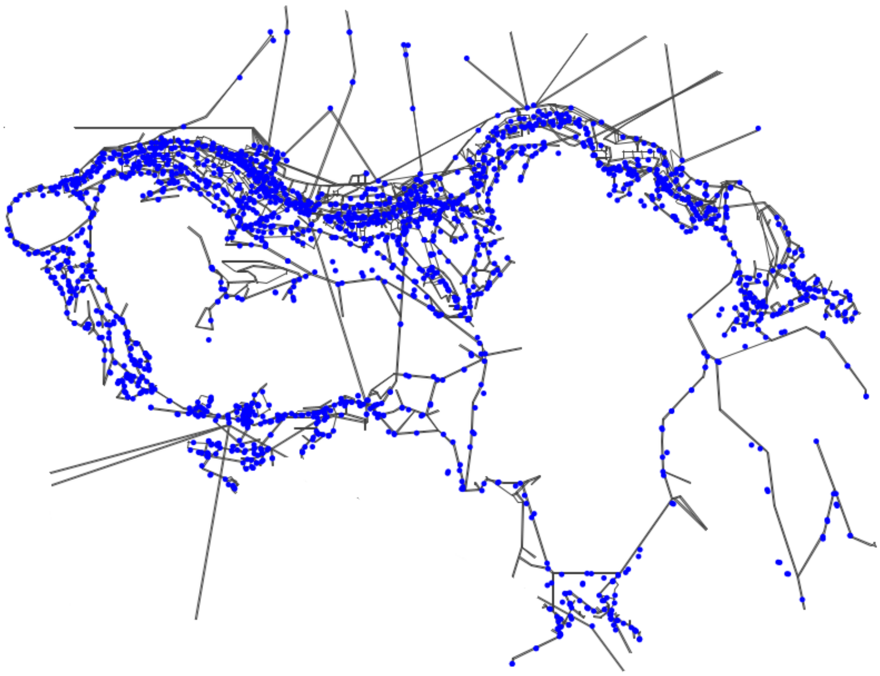

Figure 1: HKI Multimodal Network

We optimized pricing for a government owned, subsidized transit package scenario where the package includes all transit fare links in the network. The goal of the operator is to maximize social welfare while minimizing the subsidy provided. Table 1 summarizes the optimization result for the subsidized scenario.

Table 1: Optimization result (government subsidy instance)

	Package Price	Package Sold	Bus RR	MTR RR	Ferry RR
Initial	15	58,976	95%	95%	95%
Final	11.5	59,874	95.12%	99.7%	100%

Note: RR here stands for reimbursement ratio.

Table 2 shows the system performance before and after implementing the optimized priced transit package. The subsidy amount for the optimized scenario is 630,635 HKD.

Table 2: Change in system performance (government subsidy instance)

Metric	Before (Without Transit Package)	After (Optimized Transit package)	Increase	Percentage of change (%)
Total EM Utility (HKD)	528,856,489	530,756,766	1,900,277	0.36
Total system travel time (HKD)	8,256,001	8,165,795	-90,206	-1.09
Auto Trips	96,613	95,879	-735	-0.76
Transit Trips	254,017	254,947	930	0.37
Activity Number	593,171	593,305	133	0.02

The result show that the difference between EM utility improvement and subsidy provided by government is positive, i.e., social welfare improves after implementing subsidized transit package. The total number of auto trips decreased, and transit trip increased, indicating higher utilization of the transit facility after package implementation. Number of activity insertion is quite low compared to number of activities performed before implementing transit package, indicating there is very small room for demand elasticity in the case of Hong Kong.

5. CONCLUSIONS

This study proposed a flexible problem formulation and an efficient optimization framework for large-scale transit mobility package optimization. A comprehensive activity-based traffic model was developed to capture the changes in travelers' travel costs and consequent changes in their travel demand, activity pattern, route and mode choices, and finally, the resulting impacts on transport system travel time, social welfare, and operators' profitability that follow from the deployment of transit mobility packages. Numerical experiments on the Hong Kong Island multimodal network with a government subsidized all-transit package shows that implementing a well-priced transit packages can improve the overall social welfare and ensure a better utilization of the transit facilities. The numerical study can be further extended to commercial operator and network wide fare optimization which will be the focus of our future research.

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