Evaluation of optimal values of pricing and fleet sizing for integration of bike-sharing and public transportation

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SHORT SUMMARY

Bike-sharing (BS) complements public transportation (PT) by serving as an efficient first- and last-mile solution, reducing travel times, emissions, and improving health. Important factors impacting quality of service include bike availability, PT frequency, and pricing, which are design decisions. However, BS and PT decisions are often made separately, resulting in sub-optimal outcomes like insufficient bike availability or mismatched fares for combined trips. This study addresses this gap by proposing an integrated BS-PT network design problem, where design variables are optimized simultaneously to maximize social welfare. The approach balances operator surplus, user surplus, and externalities such as climate and health impacts. The problem is modeled as a bi-level program, optimizing BS fleet size, PT frequency, and fares while considering user responses in terms of demand and route flows. Numerical experiments demonstrate the benefits of this integrated approach, significantly improving social welfare compared to conventional, isolated decision-making methods.

Keywords: Bike-Sharing, Public Transportation Integration, First-and Last-Mile, Sustainable Transportation

1. INTRODUCTION

Bike-sharing (BS) has gained popularity around the world. The first BS system was launched in Amsterdam in the 1960s, and similar systems have found widespread implementation since (Lin et al., 2011). BS systems are expected to contribute to various objectives, such as reducing car usage lowering CO_2 emissions, improving public health. Furthermore, cycling participation, enhancing accessibility and mobility options which contribute to improvement of urban livability and local economies (Oeschger et al., 2020). Particularly in combination with PT, BS has potential: it may serve as a flexible and accessible first- and last-mile solution, thereby overcoming one of the main disadvantages of PT. The attractiveness of the combined mode, and thereby the demand, largely depends on the integration of these two systems. Key integration factors include (i) the supply-demand balance at stations, (ii) the frequency of PT services, (iii) pricing, for car (toll) and uni-modal and combined BS-PT trips.

Fleet sizing is a key ingredient of the BS-PT integration. Luo et al. (2023) formulated a design problem, integrating fixed-route PT and BS. The accompanying mixed-integer optimization problem determines the number of bikes per station, which allows a flexible stop choice for travelers.

Numerical experiments reveal that this integrated system offers modest efficiency improvements, particularly in lower-density areas, and that most users benefit from a high probability of bike availability (over 90%). Their results suggest that in well-designed systems, many travelers choose more distant stops to avoid transfer within the PT trip.

Design and pricing in transportation systems, particularly for PT, are deeply interconnected as financing these systems can be influenced by their price (Jara-Díaz et al., 2022). Therefore, it is crucial for decision-makers to carefully set their prices. Jara-Díaz et al. (2022) developed an optimization model to determine station spacing, capacity, fleet sizing, repositioning, fare structure, and subsidy levels for BS systems. Their study emphasizes that as BS demand grows, both station density and bike availability must increase to sustain service levels, with the optimal fare remaining relatively stable due to economies of scale, in an analysis that does not consider public transport. When BS and PT are optimized separately, conflict can arise between profit objectives for both modes (Zhang et al., 2021). Moreover, pricing strategies could actively be used to influence demand and, in turn, guide adjustments in station density and fleet sizing for BS (Zhang et al., 2021). As such, optimizing pricing for an integrated BS-PT system is a crucial aspect for multimodal transport planning decisions regarding public transport and shared mobility.

According to the literature there is a need to explore the relationship between fleet sizing and pricing in an integrated system, while accounting for both monetary and non-monetary benefits for users and operators. This research addresses this gap by analyzing the impact of fleet sizing and pricing optimization within an integrated system on operator and user monetary outcomes, overall traffic emissions, and public health outcomes.

2. METHODOLOGY

The present study aims to optimize fleet sizing and pricing for multi-modal transport systems in an urban area, focusing on the integration of BS and PT. The proposed model is a bilevel optimization problem, maximizing social welfare in the upper level. The design variables are the allocation BS fleet to the stations and the PT fleet to PT lines, as well as fare for BS, PT, combination of BS and PT (combined mode), and tolls for cars, while considering the integration of BS and PT. The lower level optimizes the user's mode choice and route choice based on the utility of each mode between each origin and destination. Figure 1 shows the framework of the bi-level optimization model, which we further discuss in the remainder of this section.

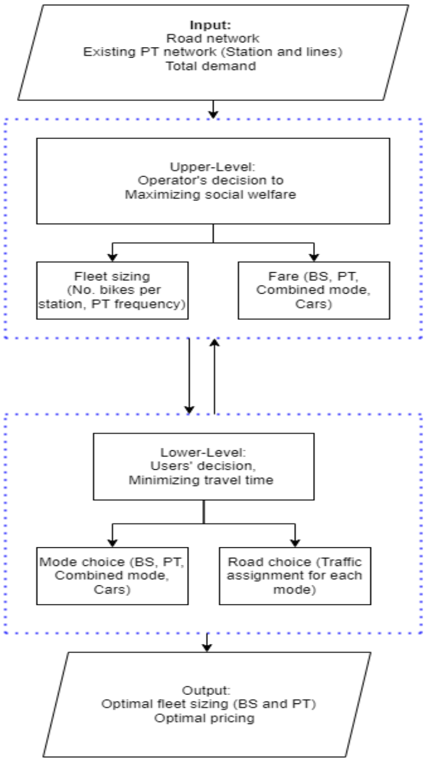

Figure 1: Bi-level optimization model framework

Mathematical model

The mathematical model focuses on making strategic decisions to enhance social welfare through the optimal allocation of fleets and pricing strategies for urban multi-modal transport systems. The objective function of the upper-level problem is social welfare, consisting of three components: operator surplus, consumer surplus, and externalities.

Operator surplus is the difference between their revenue and costs. The operator's revenue is the collected fares of BS, PT and the combined mode, and tolls for cars. The cost for operators consists of the price of purchasing vehicles and running cost for BS and PT (fuel consumption, tyres, maintenance, and so forth). In our model, operator surplus is formally defined as

$$OS = \sum_{m\in M}\sum_{w\in W}\Delta_m . q_w^m - (\sum_{m\in M} C_v^{bs,pt} . N_{bs,pt} + \sum_{m\in M}\sum_{a\in A} C_r^{bs,pt} . L_a \times N_{bs,pt}) \quad (1)$$

Here, the first term is the income for the operator from the BS, PT, cars and combined modes. In this equation we denote by m$\in \{bs, pt, c, cb\}$ the mode, being either BS (*bs*), PT (*pt*), car (*c*), or combined mode (*cb*). Origin-destination pairs in the network are denoted by $w \in W$, with corresponding *m*-dependent demand q_w^m. Demand is a dependent variable in the lower-level problem. We denote a link in the network by $a \in A$, with L_a the corresponding length of the link. $C_v^{bs,pt}$ is cost of vehicles for BS and PT, and $C_r^{bs,pt}$ is the cost of running of vehicles for BS and PT. And the design variables are the fare of mode *m*, Δ_m and the fleet size for BS and PT, which are N_{bs} and N_{pt}, respectively.

Consumer surplus measures the difference between the price consumers pay for a service and the price they are willing to pay. The standard form of consumer surplus assuming a multinomial logit model for modal choice is as follows:

$$CS = \sum_{w \in W} \frac{q_w}{m_u} . \ln\left(\sum_{m \in M} e^{U_w^m}\right) + B_0 \tag{2}$$

Here, m_u is the marginal utility, and U_w^m is the utility function of mode *m* for a trip for origin-destination pair *w*. B_0 is a constant that shift the absolute level of the consumer surplus, and it can be set as zero given that it does not influence the optimization problem. Urban mobility has both negative and positive impacts. Negative effects include air pollution, greenhouse gas emission, noise pollution, and land use consumption, while positive effects, particularly from active transportation like biking, contribute to fitness and health. These impacts are considered externalities of the transportation systems. In this study, we consider externalities including climate change and health benefits. We include the cost related greenhouse gas emissions from motor vehicles, and the health benefits as a result of cycling.

To assess the energy use and environmental impacts of transportation, Life Cycle Assessment (LCA) is commonly used. LCA evaluates the environmental impact of transportation systems through three main components: vehicle component (manufacturing, delivery, maintenance, and disposal of vehicles), the fuel component (production, distribution, and end-use of fuel), and the infrastructure component (construction, maintenance, and disposal of transportation infrastructure).

$$CC = \sum_{a \in A} SC_{CO2} . (\sum_{m \in M} L_a . y_a^m . (Vc_m + Fc_m + Ic_m)) \tag{3}$$

The above formula shows the climate change cost externality. In this formula, SC_{CO2} is the social cost of CO_2, which is measure that estimates the economic harm caused by adding more CO_2 to the atmosphere. Vc_m, Fc_m, Ic_m are the vehicle, fuel and infrastructure components, achived from LCA, for each mode of transportation. And y_a^m is the number of passengers on link *a* using mode *m*, which is a dependent variables achieves from the lower-level problem.

$$HB = \sum_{a \in A} \varepsilon . (L_a . y_a^{bs} . t_a^{bs}) \tag{4}$$

This shows the health benefits formula. In this equation, t_a^{bs} is the travel time of BS on link a, and ε is the health benefit constant that shows the monetary benefit of using cycling as a mode of transportation.

The lower-level problem relates to the users' decisions for mode and route choice. To this end, we adopt an assignment with elastic demand. The modal split is determined based on a logit model, the mode-specific route flows are in (user) equilibrium.

The proposed bi-level optimization model is NP-hard, making it difficult to solve directly using exact methods. We use a Genetic Algorithm (GA) to solve the problem at hand. GAs are population-based methods, iteratively finding candidate solutions by applying operators based on natural selection and genetic recombination (Agrawal et al., 2004). The lower-level problem is numerically solved using Method of Suggestive Average (MSA).

Numerical experiments are executed to evaluate the (de)merits of BS-PT integration. To this end, we use Mandl's (Mandl, 1979) 15-node Swiss network as shown inFigure. 2. Nodes are origins and destinations (stations in the case of PT).

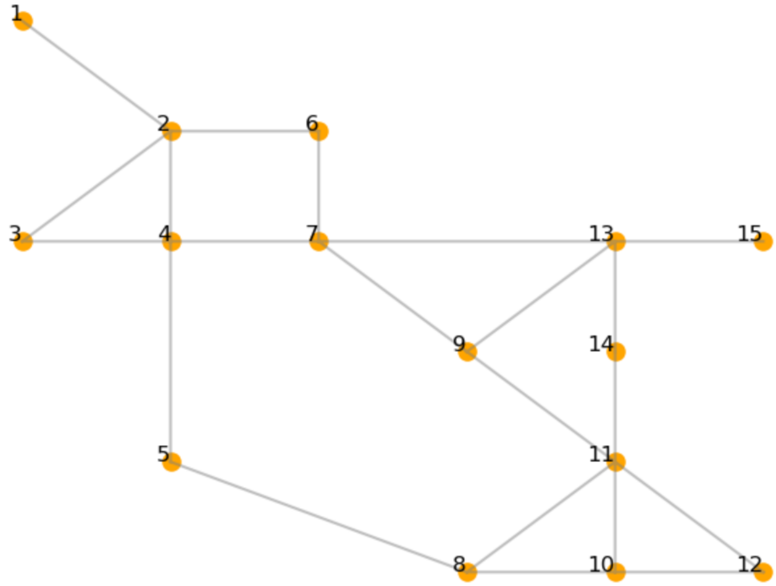

Figure 2: Illustration Mandl's Swiss Network

For illustration of our model, we will consider three PT lines in the network, as shown in Figure 3.

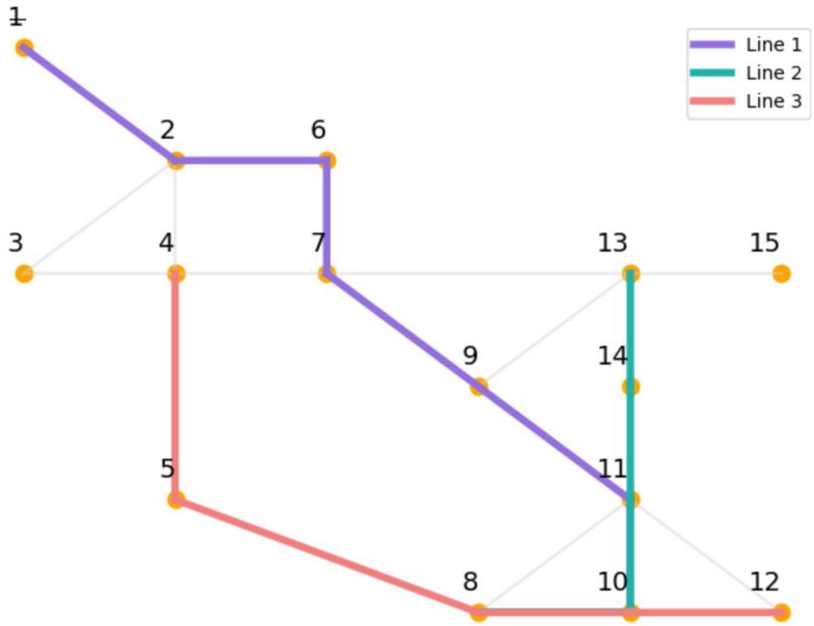

Figure 3. Public transportation lines

3. RESULTS AND DISCUSSION

Currently, the upper-level problem has been solved under the assumption of free flow traffic for cars. This solution serves as a baseline to understand if the upper-level algorithm is working in a logical way. The logit model of the existing condition shows the following modal split:

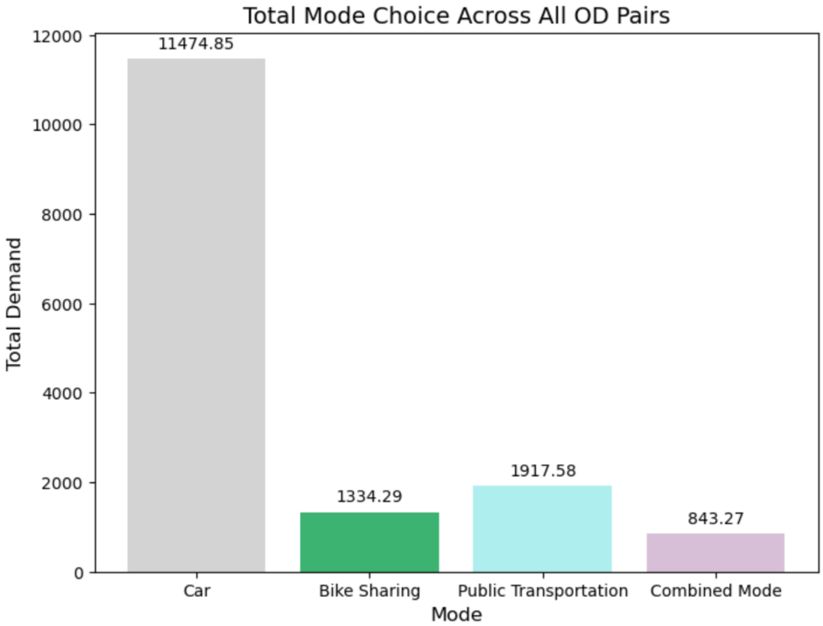

Figure 4: Modal split in the current situation

These values are achieved by setting the pricing for all modes random values as follows: BS fare in range of (1.0 , 5.0) Euro, PT fare (3.0, 20.0) Euro, Cars toll (5.0, 30.0) Eur, and Combined mode fare (2.0, 15.0) Euro

The initial results indicate a greater proportion of car usage compared to other modes of transportation, with public transportation occupying the second position.

It is expected that fully solving the model will yield an optimal pricing strategy for all modes, effectively balancing the trade-off between user benefits and operator benefits. Notably, our model also accounts for the health benefits of cycling. In the process of solving the model, we explore the distinction between treating health benefits as an external value (factored into the social welfare function) versus an internal value included in the utility function of bike-sharing.

Solving the upper-level problem alone with this initial assumptions leads to the following results:

Results of pricing shows that the optimal values for fare of each mode of transportation in the first round of upper-level optimization is as follows: BS fare 2 Euros, cars tolls 13 Euros, PT fare 4 Euros, and combined mode fare is 13 Euros. It is worth mentioning that in this first round of running the model no limitation was considered in the pricing of modes. Showing that to have more realistic results we need some assumptions and limitations on the pricing values for each mode. Results of pricing shows that the optimal values for fare of each mode of transportation in the first round of upper-level optimization is as follows: BS fare 15 Euros, cars tolls 29 Euros, PT fare 2 Euros, and combined mode fare is 8 Euros. It is worth mentioning that in this first round of running the model no limitation was considered in the pricing of modes. Showing that to have more realistic results we need some assumptions and limitations on the pricing values for each mode.

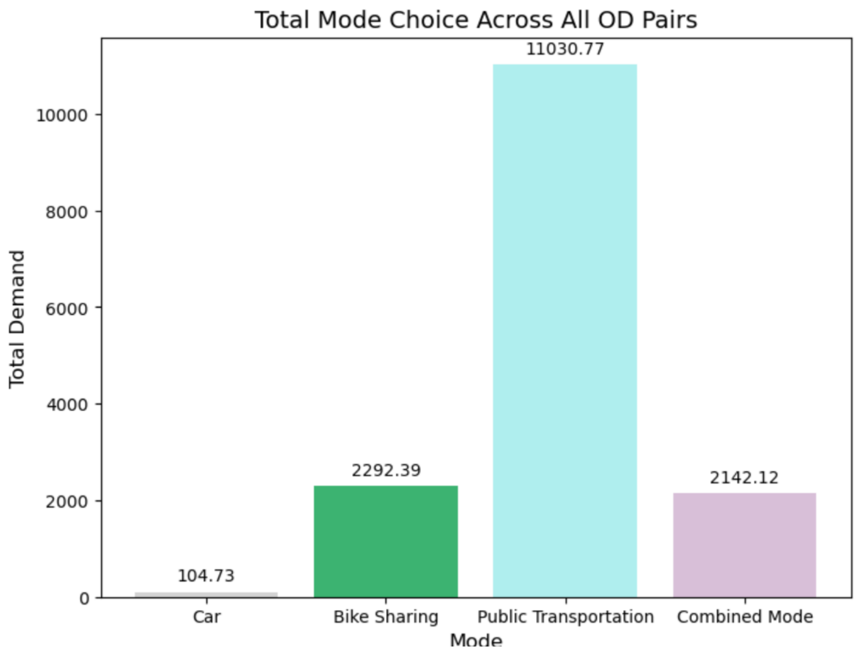

Figure 5. Modal split after first round of upper-level optimization

As shown in Figure 5, implementing tolls for cars results in a significant reduction in the number of cars in the modal split. Meanwhile, the demand for the combined mode also decreases, indicating that to fully leverage the efficiency of this mode, more detailed assumptions about the design variables are needed to better capture its characteristics.

Figure 6 and 7 shows the number of bike-sharing per station and Public transportation fleet sizing per line.

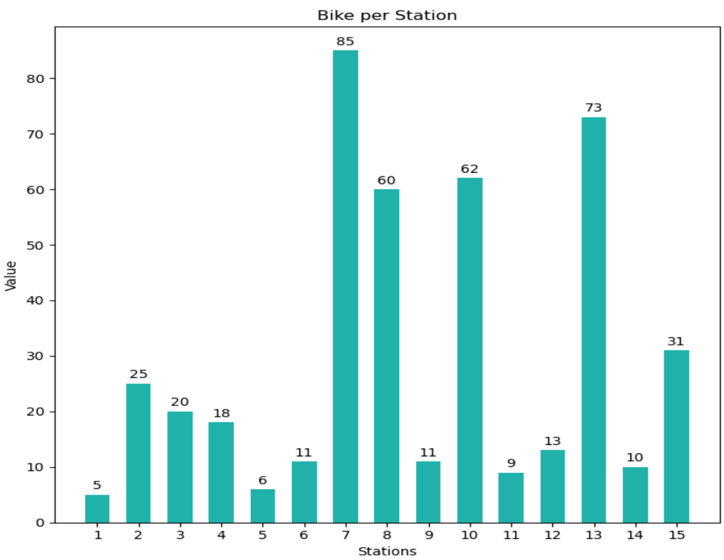

Figure 6: Number of BS per stations

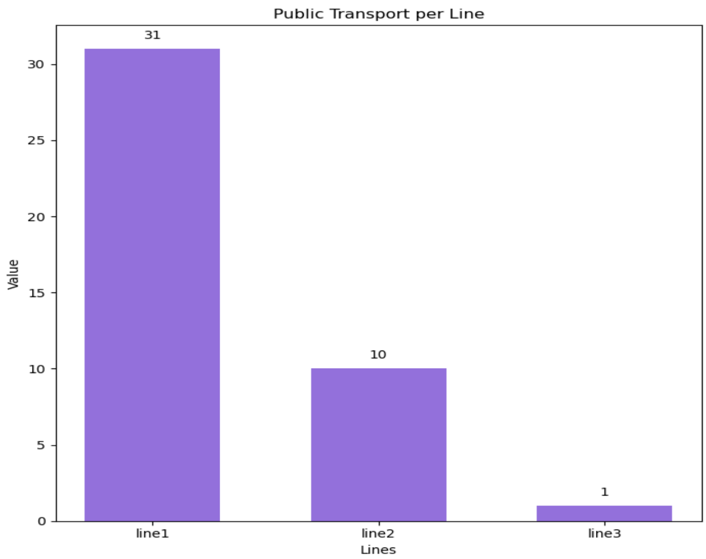

Figure 7: Fleet sizing for PT per line

In the future, to assess the impact of pricing on demand and fleet sizing, the pricing strategy will be evaluated based on the trip length. Additionally, the effects of decision variables on pollutant emissions and the health benefits derived from cycling will also be examined.

4. CONCLUSIONS

In this paper, a multi-modal transportation network design problem, which incorporates public transportation, bike-sharing, and cars, was developed. The accompanying optimization problem is bi-level in nature. The program optimizes the number of bikes per station, public transportation frequency, and fare of each mode of transportation, while accounting for behavioral choices of users in response to these design decisions. The model will analyse: (1) changes in emission rate, (2) improvement in public health, (3) optimal value for number of BS and PT frequency, and (4) optimal pricing for transportation modes.

The main conclusions of the optimization model are as follows:

1. Emission reduction: One of the key expected results of this study is the reduction in emissions. In fact, the optimization of BS fleet size, PT frequency, and fare structure will promote greater use of sustainable transportation modes, thus it will lead to a decrease in the emission rate from the transportation.

2. Public Health: The study also considers the health benefits from the active mode of transportation as externalities in the social welfare objective function. We expect that in model will lead to more BS demand portion and in this way enhance the total health benefit.

3. Increase overall benefits of the system (social welfare): The optimization model of this study aims to provide a more efficient integrated transportation system by optimizing the bike availability, PT frequency, and fare of transportation modes.

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