Promoting Public Transport Utilization through an Incentive Strategy for Dynamic Demand Management

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Short summary

Seamless multimodal transport systems play a critical role in developing sustainable urban mobility. We propose an incentive-based strategy as a tool for modal shift towards sustainable mobility choices in a multimodal setting under a constrained budget. A key feature of the proposed framework is that individual origin–destination trips may be completed through a genuine combination of car and public transport, reflecting the park-and-ride travel patterns observed in real urban networks. By developing an optimization framework, we seek to maximize social benefits and network efficiency, while adhering to a budget constraint, ensuring cost-effective and scalable solutions for sustainable urban mobility. The methodology is tested on a network simulating the Jätkäsaari area, a peninsula in the city of Helsinki, Finland. The results show that, at the break-even point of the cost-benefit analysis, i.e., approximately 1 500 hours, the total travel time is reduced by more than 30%, while it peaks at 56.02% for a budget of 10 000 hours. Such results correspond to an increase in total usage of public transport from approximately 11 to 23.43 percentage points, respectively. This indicates that even a small investment in the incentive policy can result in a significant improvement in the network efficiency.
Keywords: Multi-modal transport, pricing and capacity optimization, traffic management, and sustainable mobility.

1 Introduction

Seamless multimodal transport is a cornerstone of sustainable urban mobility transition (Banister, 2008). Seamless mobility is defined by reduced travel time and enhanced user convenience, among other characteristics (Lee et al., 2025). By providing residents with a seamless multimodal transport system, namely one in which individual trips may combine private vehicles, public transport (PT), and active travel within a single journey, policymakers can facilitate the long-desired modal shift in favor of sustainable travel. A central challenge in achieving this shift is the optimal allocation of limited policy resources across a heterogeneous network in which travelers choose among modes, routes, and combinations thereof.

Incentive-based strategies have received considerable attention as a means of influencing urban travelers' modal choices. Economic incentives, such as monetary subsidies or exchangeable credits, have been shown to increase PT ridership (Guzman & Hessel, 2022), reduce peak-hour car traffic (Sun et al., 2020), and facilitate mode shift more broadly (de Kruijf et al., 2018; Yan et al., 2024). The evidence suggests that economic incentives outperform non-economic interventions when sustained behavioral change is the objective (Salihou et al., 2022; Vosough & Roncoli, 2024), and that personalized, budget-aware schemes can improve both impact and cost-effectiveness (Xiong et al., 2020). Through reducing the share of unsustainable travel modes, such schemes contribute to lowering CO_2 emissions (Raux et al., 2021). More recently, Liu et al. (2024) proposed a personal carbon trading travel incentive mechanism that derives its budget from the carbon emission reductions generated by commuters' mode shifts, and optimizes incentive allocation via a Stackelberg game model embedded within a multi-mode traffic flow equilibrium. Yet most existing studies remain mode-specific or corridor-focused, and integrated optimization frameworks for allocating incentive budgets across competing modes and origin–destination (OD) pairs in a network setting are still lacking (de Kruijf et al., 2018; Chen et al., 2022).

A further, and in our view more fundamental, limitation of the existing literature concerns the representation of travel behavior itself. Most network models treat trips as unimodal: each traveler

is assigned exclusively to either a car or a PT itinerary for the entire journey. Yet a substantial share of urban trips are performed in a genuinely combined fashion, whereby the first leg is driven to a park-and-ride (P&R) facility and the remainder is completed by PT. Modeling this type of intermodal travel in a network equilibrium framework has been addressed in a strand of literature going back to Fernández et al. (1994), who formulated a user equilibrium that included combined modes and modeled the choice of transfer node via a nested logit model. García & Marín (2005) extended this to asymmetric cost functions using a two-stage nested logit formulation, and Li et al. (2007) further developed the equilibrium model to accommodate elastic demand and passengers' discomfort on crowded transit vehicles. Pineda et al. (2016) proposed an integrated traffic-transit stochastic equilibrium model with P&R facilities that jointly captures the uncertainty travelers face across both road and transit subnetworks. On the algorithmic side, Fan et al. (2022) developed a large-scale combined mode-split and traffic assignment (CMSTA) framework that explicitly accommodates car-to-transit intermodal modes, and Fan et al. (2024) subsequently proposed a path-based unified equilibrium model using a cross-nested logit formulation capable of handling large real-world networks with P&R interchanges. Despite this body of work, however, all of these contributions share a common feature: they model how travelers distribute across modes and routes under given network conditions, but do not optimize any policy instrument, such as incentive schemes under a budget constraint, in response to that equilibrium. The integration of intermodal assignment frameworks with incentive optimization remains, to the best of our knowledge, entirely unexplored.

This paper addresses both gaps identified above. Building on the incentive optimization framework introduced by Ivanova et al. (2025), which was validated on the Nguyen–Dupuis network under exclusively unimodal OD assignment, the present work extends the methodology in three directions: (i) a more tractable model of PT crowdedness, requiring fewer parameters that may be difficult to observe in practice; (ii) a reformulation of the PT modal share that exactly equals zero—rather than a small residue resulting from the logit formulation—when no PT line is available for a given OD pair; and, most significantly, (iii) allowing OD trips to be performed in a genuinely multimodal fashion, by permitting combinations of car and PT within a single journey. The framework is applied to a real-world case study, the Jätkäsaari peninsula in Helsinki (Finland), to provide insights into its impact on traffic management decision-making and to demonstrate that even modest incentive budgets can yield substantial improvements in network efficiency.

2 Methodology

This section formulates an optimization problem to find the optimal incentives, in the form of monetary rewards per OD pair, that, by encouraging PT use, minimize passenger total travel time across the network, considering car, PT, and combinations of both, i.e., via a park-and-ride (P&R) facility, subject to a given budget limit.

The transport network is defined by a graph $G(V, A)$, where V is the set of nodes and $A \subset V \times V$ is the set of links. Let $W \subset V \times V$ be the set of OD pairs, and let us assume the networks accommodate two modes, car and PT, while the trips can be performed in three different ways, namely unimodal by car, unimodal by PT, and multimodal, using a car first and then public transport after a P&R transfer. The incentive is allocated only to PT to reduce car usage. If PT covers the entire trip, the incentive applies to the full journey; otherwise, in multimodal trips, it applies only to the PT segment after the P&R facility. Let the travel demand, D_w, be described by the fixed total number of trips (irrespectively of the mode) between the OD pair $w \in W$. In order to allow a transfer from one mode to another in the problem, let us identify some nodes $v \in V$ (or possibly add new ones) that represent transfer hubs, such as a P&R facility, and some ODs $w \in W$ that can be served by the multimodal option, possibly adding a slightly detoured path $p \in P_w$, where P_w is the set of available paths for OD w. The key idea is to split such ODs into two virtual ones so that the first leg of the OD—from origin to the P&R facility—can be traversed by car and the second one—from the P&R facility to the destination—can be traversed by PT. Then, let us name the set of *existing* ODs as W^{E} to distinguish them from the set of *virtual* ODs W^{V}, with the latter including the newly generated ODs from splitting the existing ODs. Consequently, we redefine W as the set of all ODs, namely, $W^{\mathrm{E}} \cup W^{\mathrm{V}} \subseteq W$, and $W^{\mathrm{E}} \cap W^{\mathrm{V}} = \emptyset$. Moreover, we denote the set of ODs that can carry PT lines for the whole trip as $W^{\mathrm{PT}} \subset W^{\mathrm{E}} \cup W^{\mathrm{V}}$, the set of ODs that can carry car flows for the whole trip as $W^{\mathrm{C}} \subset W^{\mathrm{E}} \cup W^{\mathrm{V}}$, and the set of ODs that can carry a *multimodal* combination of car and PT as $W^{\mathrm{M}} \subset W^{\mathrm{E}}$. Notice that ODs $w \in W^{\mathrm{V}}$ are generated by splitting ODs $w \in W^{\mathrm{M}}$. Given $w \in W^{\mathrm{M}}$, we define $w^{\mathrm{C}} \in W^{\mathrm{C}} \cap W^{\mathrm{V}}$ the first part

of the split OD w that will carry car traffic, and $w^{\mathrm{PT}} \in W^{\mathrm{PT}} \cap W^{\mathrm{V}}$ the second (and last) part of the split OD w that will carry PT traffic. Conversely, given $w \in \left\{W^{\mathrm{C}} \cap W^{\mathrm{V}}\right\} \cup \left\{W^{\mathrm{PT}} \cap W^{\mathrm{V}}\right\}$, we define $w_w \in W^{\mathrm{M}} \subset W^{\mathrm{E}}$ the multimodal existing OD it refers to.
The optimization problem subject to a budget constraint B is formulated as:

$$\min_{I^{\mathrm{PT}},f} \quad \left(\sum_{w \in W^{\mathrm{PT}}} \left(q_w^{\mathrm{PT}} \cdot t_w^{\mathrm{PT}}\right) + \sum_{a \in A} \left(x_a \cdot t_a\right) \right) \tag{1}$$

$$\text{s.t.} \quad \sum_{w \in W^{\mathrm{PT}}} q_w^{\mathrm{PT}} \cdot I_w^{\mathrm{PT}} \leq B \tag{2}$$

$$q_w^{\mathrm{PT}} = \begin{cases} D_w \cdot \frac{e^{-U_w^{PT}}}{e^{-U_w^{C}} + e^{-U_w^{PT}}}, & \text{if } w \in W^{\mathrm{PT}} \cap \left(W^{\mathrm{E}} \setminus W^{\mathrm{M}}\right) \\ D_{w_w} \cdot \frac{e^{-U_{w_w}^{\mathrm{M}}}}{e^{-U_{w_w}^{\mathrm{C}}} + e^{-U_{w_w}^{\mathrm{M}}}}, & \text{if } w \in W^{\mathrm{PT}} \cap W^{\mathrm{V}} \text{ and } w_w \notin W^{\mathrm{PT}} \\ D_{w_w} \cdot \frac{e^{-U_{w_w}^{\mathrm{M}}}}{e^{-U_{w_w}^{\mathrm{C}}} + e^{-U_{w_w}^{\mathrm{PT}}} + e^{-U_{w_w}^{\mathrm{M}}}}, & \text{if } w \in W^{\mathrm{PT}} \cap W^{\mathrm{V}} \text{ and } w_w \in W^{\mathrm{PT}} \\ D_w \cdot \frac{e^{-U w^{\mathrm{PT}}}}{e^{-U_w^{\mathrm{C}}} + e^{-U_w^{\mathrm{PT}}} + e^{-U_w^{\mathrm{M}}}}, & \text{if } w \in W^{\mathrm{PT}} \cap W^{\mathrm{M}} \\ 0, & \text{if } w \notin W^{\mathrm{PT}} \end{cases}, \quad \forall w \in W \tag{3}$$

$$U_w^{\mathrm{PT}} = \beta_0 + \beta_1 \cdot t_w^{\mathrm{PT}} + \beta_2 \cdot t_w^{\mathrm{WT}} + \beta_3 \cdot \phi_w - \beta_4 \cdot I_w^{\mathrm{PT}}, \qquad \forall w \in \left(W^{\mathrm{PT}} \cap W^{\mathrm{E}}\right) \cup W^{\mathrm{M}} \tag{4}$$

$$U_w^{\mathrm{C}} = \beta_5 \cdot t_w^{\mathrm{C}}, \qquad \forall w \in \left(W^{\mathrm{PT}} \cap W^{\mathrm{E}}\right) \cup W^{\mathrm{M}} \tag{5}$$

$$U_w^{\mathrm{M}} = \beta_6 + \beta_5 \cdot t_{w^{\mathrm{C}}}^{\mathrm{C}} + \beta_1 \cdot t_{w^{\mathrm{PT}}}^{\mathrm{PT}} + \beta_2 \cdot t_{w^{\mathrm{PT}}}^{\mathrm{WT}} + \beta_3 \cdot \phi_{w^{\mathrm{PT}}} - \beta_4 \cdot I_{w^{\mathrm{PT}}}^{\mathrm{PT}}, \qquad \forall w \in W^{\mathrm{M}} \tag{6}$$

$$t_w^{\mathrm{WT}} = \begin{cases} t_w^{\mathrm{TT}} + \left\lceil \frac{q_w^{\mathrm{PT}}}{N_w} \right\rceil \cdot \frac{h_w}{2}, & \text{if } w \in W^{\mathrm{PT}} \cap W^{\mathrm{V}} \\ \left\lceil \frac{q_w^{\mathrm{PT}}}{N_w} \right\rceil \cdot \frac{h_w}{2}, & \text{otherwise} \end{cases}, \qquad \forall w \in W^{\mathrm{PT}} \tag{7}$$

$$\phi_w = e^{\frac{q_w^{\mathrm{PT}}}{N_w}} - 1, \qquad \forall w \in W^{\mathrm{PT}} \tag{8}$$

$$t_p^{\mathrm{C}} = \sum_{a \in A} \delta_{a,p,w} t_a, \qquad \forall p \in P_w, w \in W \tag{9}$$

$$\sum_{a \in A} \delta_{a,p,w}\, t_a \;-\; u_w \;\geq\; 0, \qquad \forall p \in P_w, w \in W \tag{10}$$

$$\left(\sum_{a \in A} \delta_{a,p,w}\, t_a \;-\; u_w \right) \; f_w^p \;=\; 0, \qquad \forall p \in P_w, w \in W \tag{11}$$

$$t_a = t_a(x_a), \qquad \forall a \in A \tag{12}$$

$$x_a = \sum_{p \in P_w} \sum_{w \in W} \delta_{a,p,w} \cdot f_w^p, \qquad \forall a \in A \tag{13}$$

$$\sum_{p \in P_w} f_w^p = \begin{cases} D_w - q_w^{\mathrm{PT}}, & \text{if } w \in W^{\mathrm{E}} \setminus W^{\mathrm{M}} \\ q_{(w_w)^{\mathrm{PT}}}^{\mathrm{PT}}, & \text{if } w \in W^{\mathrm{C}} \cap W^{\mathrm{V}} \\ D_w - q_{w^{\mathrm{PT}}}^{\mathrm{PT}} - q_w^{\mathrm{PT}}, & \text{if } w \in W^{M} \\ 0, & \text{if } w \in W^{\mathrm{PT}} \cap W^{\mathrm{V}} \end{cases}, \qquad \forall w \in W \tag{14}$$

$$I^{\mathrm{PT}},\; f \geq 0 \tag{15}$$

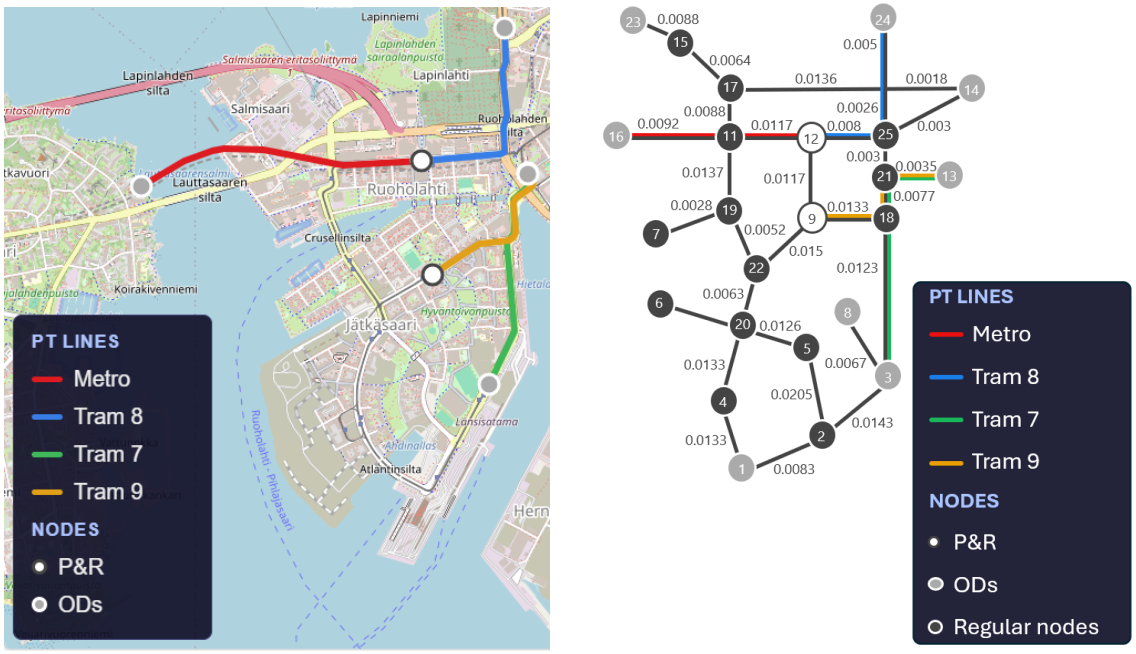
The objective function (1) minimizes the total network travel time for both car and PT travelers. The share of demand accommodated by PT on OD w is denoted as q_w^{PT}, while t_w^{PT} is the respective travel time. The car flow on link a is denoted by x_a, while t_a is the respective travel time. Constraint (2) limits the incentives, I_w^{PT}, allocated to OD w within the budget B. In order to determine the share of PT q_w^{PT} with respect to the fixed demand D_w on OD w, we use a logit formulation. Let us consider the five possible cases defined in (3). The first case is for existing ODs that carry PT lines for the whole trip and cannot be split for multimodal purposes, namely $w \in W^{\mathrm{PT}} \cap \left(W^{\mathrm{E}} \setminus W^{\mathrm{M}}\right)$: then q_w^{PT} results from a logistic function weighing the car and the PT options according to their respective disutility U_w^{C} and U_w^{PT}. The second case is for virtual ODs whose corresponding existing OD does not have PT lines for the whole trip, namely $w \in W^{\mathrm{PT}} \cap W^{\mathrm{V}}$ and $w_w \notin W^{\mathrm{PT}}$: then q_w^{PT} results from a logistic function weighing the car and the multimodal options according to their respective disutility $U_{w_w}^{\mathrm{C}}$ and $U_{w_w}^{\mathrm{M}}$, where we highlight

that such disutilities are calculated on w_w, i.e., the OD where the virtual w originated from. The third case is for virtual ODs whose corresponding existing ODs include PT lines for the whole trip, namely $w \in W^{\mathrm{PT}} \cap W^{\mathrm{V}}$ and $w_w \in W^{\mathrm{PT}}$: then q_w^{PT} results from a logistic function weighing the car, the PT, and the multimodal options according to their respective disutility $U_{w_w}^{\mathrm{C}}$, $U_{w_w}^{\mathrm{PT}}$, and $U_{w_w}^{\mathrm{M}}$. The fourth case is for ODs which can offer PT lines for either of the whole trip or the final part of it in a multimodal fashion, namely $w \in W^{\mathrm{PT}} \cap W^{\mathrm{M}}$: then q_w^{PT} results from a logistic function weighing the car, the PT, and the multimodal options according to their respective disutility U_w^{C}, U_w^{PT}, and U_w^{M}. Finally, the fifth case is for the ODs which do not offer any PT option: then q_w^{PT} is 0. The disutility of car, PT and multimodal option, U_w^C, U_w^{PT}, and U_w^M, are computed by (5), (4), and (6), respectively. The car disutility is based on the car travel time The PT disutility is a summation of the PT travel time t_w^{PT}, waiting time t_w^{WT}, crowdedness cost ϕ_w, minus incentive value I_w^{PT}, weighed by the coefficients β_0, β_1, β_2, β_3, and β_4. We assume that the PT between OD pair w is operating in an exclusive lane; therefore, t_w^{PT} is fixed and independent of car traffic. Constraint (7) calculates the waiting time t_w^{WT} for PT between OD pair w, through headway h_w, and PT vehicle capacity N_w—a sum of seating and standing capacity in a PT vehicle. In the multimodal case, hence when $w \in W^{\mathrm{PT}} \cap W^{\mathrm{V}}$, a transfer time t_w^{TT} is also added. t_w^{C}, where β_5 is a coefficient defining the behavior of the drivers. The disutility for the multimodal ride is calculated by applying the car disutility to the first part of the trip, namely along w^{C}, and the PT disutility for the second part, namely along w^{PT}, where PT waiting time t_w^{TT}, includes the transfer time between modes. Constraint (8) defines PT crowdedness ϕ_w between OD pair w, as a function of the PT share q_w^{PT}, and the total vehicle capacity N_w. As soon as PT ridership begins, ϕ_w grows exponentially to the passenger load factor $\frac{q_w^{\mathrm{PT}}}{N_w}$, capturing the empirically observed non-linear perception of crowding in PT. Once q_w^{PT} approaches the full capacity N_w, the exponential term rises the crowdedness value steeply, endogenously discouraging solutions that push PT demand beyond its effective capacity and balancing car-to-PT modal shifts against service quality degradation. By subtracting 1, ϕ_w is zero when no passengers ride. The car travel time t_p^{C} is defined in (9), where $\delta_{a,p,w}$ is a binary indication that equals 1 if link a is located on path p between OD pair w, and 0 otherwise. Constraints (10) and (11) are complementarity constraints for ensuring user equilibrium car flow pattern, i.e., Wardrop's first principle. Link travel times are defined in (12) as a function of link flows. Constraint (13) maps path flows to link flows, while (14) ensures flow conservation, i.e., all demand is distributed between car, PT, or multimodal routes. For the latter, we identify four cases. The first case is for all the existing ODs that do not provide a multimodal option, namely $w \in W^{\mathrm{E}} \setminus W^{\mathrm{M}}$: then the car flow on OD w, defined as $f_w = \sum_{p \in P_w} f_w^p$, results from the difference between the demand D_w and the share of PT q_w^{PT}. The second case is for all the virtual ODs representing the part of w performed by car, namely $w \in W^{\mathrm{C}} \cap W^{\mathrm{V}}$: then the car flow on OD w is the same as the share of PT for the second part of the trip, i.e. $q_{(w_w)^{\mathrm{PT}}}^{\mathrm{PT}}$. The third case is for all the ODs that do provide a multimodal option, namely $w \in W^{\mathrm{M}}$: then the car flow on OD w results from the difference between the demand D_w, and the share of PT for the whole trip q_w^{PT} plus the share of PT for the multimodal option $q_{w^{\mathrm{PT}}}^{\mathrm{PT}}$. The fifth case is for all the virtual ODs that carry PT, namely $w \in W^{\mathrm{PT}} \cap W^{\mathrm{V}}$: then the car flow on OD w is 0. Finally, (15) ensures non-negativity for incentive value, i.e., no toll, and for the flow of cars taking path $p \in P_w$.

3 Results and discussion

Setup

To solve the optimization problem (1)–(15), we use the AMPL modeling language and the Gurobi solver through the Python programming language, obtaining optimal solutions for all tested instances. The network, depicted in Figure 1, models the Jätkäsaari area in Helsinki that hosts the busiest passenger ports in the city with ferries departing to/arriving from Tallinn, Estonia. This network contains 30 links and 24 nodes, 9 of which are origins/destinations. The set W^{E} contains 19 existing OD pairs. Only 2 of the existing ODs offer a PT option for the whole trip and, therefore, are contained in both W^{C} and W^{PT}. We can identify 2 ODs that can be performed by the multimodal options and, therefore, are contained in W^{M}. Therefore, the latter can be split into 2 virtual ODs each. The link volume-delay function in the tested network is calculated through the BPR function (Bureau of Public Roads (1964)), $t_a(x_a) = t_a^0 \left(1 + 0.15\,(x_a/c_a)^4\right)$, where t_a^0 is the free flow travel time in link a and c_a is its capacity in vehicles per time unit. The disutility functions parameters are set as $\beta_0 = -0.1$, $\beta_1 = -0.3$, $\beta_2 = -0.3$, $\beta_3 = -0.2$, $\beta 4 = -5.0$, $\beta_5 = -0.1$, and $\beta_6 = -0.3$, in accordance to Wardman et al. (2016) and Börjesson & Rubensson (2019).



(a) (b)

Figure 1: The network used for the simulations with its PT lines highlighted. (a) A map of the Jätkäsaari area. (b) The underlying graph utilized. The values on each edge represent the free flow travel time for cars in hours. The travel time for the PT lines are: 0.0333 hours (Metro), 0.05 hours (Tram 8), 0.0667 hours (Tram 7), and 0.05 hours (Tram 9).

Results under Different Budgets

Figure 2a shows the changes in the objective function—representing the total travel time—as the budget B allocated for PT incentives increases. It decreases sharply with initial increases in B, then plateaus. This change is representative of diminishing marginal returns in system performance from increasing the incentive budget. The non-linear trend reflects the saturating effect of incentives on shifting demand toward PT, consistent with the logistic formulation of the mode choice constraint (3). Thus, even a small investment in the incentive policies can result in a significant improvement in the network efficiency. This is especially true considering that the network shows improvements even though it provides only two ODs served by PT and two by a combination of car and PT. Although the impact of the change is dependent on the size of the network, it does present an appealing economic rationale behind incentive schemes. Figure 2b shows the percentage of PT usage relative to the total demand that could be served by PT—the two ODs that carry PT for the whole trip $w \in W^{\mathrm{C}} \cap W^{\mathrm{PT}}$ and the two virtual ODs resulting from splitting the existing multimodal ones $w \in W^{\mathrm{PT}} \cap W^{\mathrm{V}}$—as a function of B. We can see an increase of 23.43 percentage points from 23.45% to 46.88%. The relationship is concave, with rapid increases in PT share at low budgets, and saturation at higher levels. Therefore, even with relatively small investments in the incentive schemes, the overall network can achieve an increase in PT ridership and a sustainable mobility shift. Figures 2c and 2d show that budgets where benefits exceed costs also achieve more than half of the potential travel time reduction. At the break-even point—approximately 1 500 hours—the total travel time is reduced by more than 30%, while it peaks at 56.02% for a budget of 10 000 hours. Using, for example, Finland's value of time[1], this corresponds to an investment of 10 305 euros to achieve a 30% reduction relative to a no-incentive baseline. Beyond this level, costs rise with diminishing returns, indicating an optimal budget threshold.

[1] `https://www.doria.fi/handle/10024/179995`

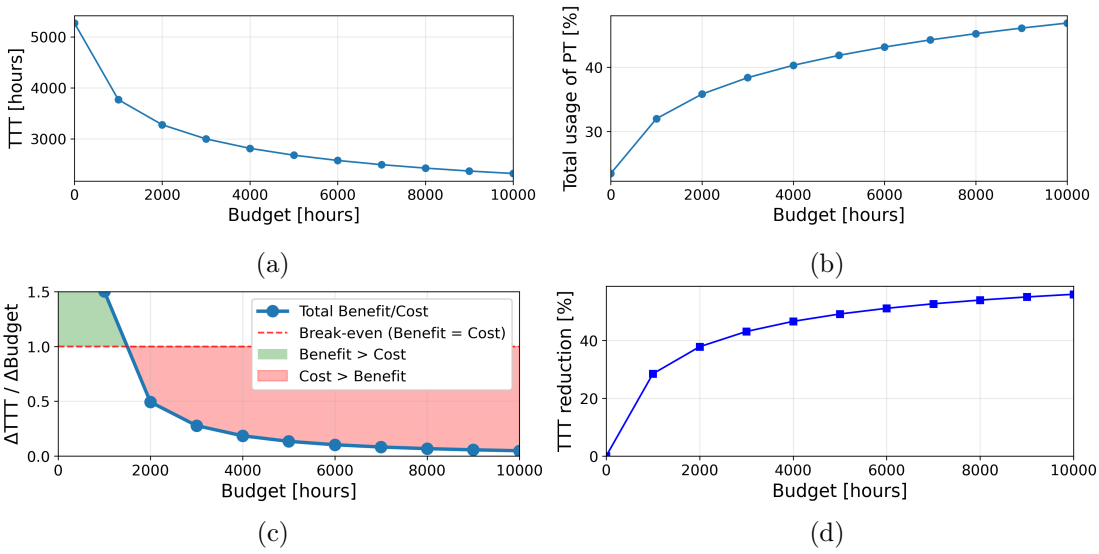


Figure 2: Sensitivity analysis as the budget increases for the: (a) total travel time, (b) usage percentage of PT, (c) benefit/cost ratio defined as the ratio between variations of total travel time and budget, and (d) total travel time reduction.

4 Conclusions

By applying the proposed methodology to the study area, we demonstrated the effectiveness of implementing incentive strategies to reduce congestion by redistributing the traffic within different modes, with a particular focus on promoting a sustainable modal shift. Although not discussed in the present paper, it is straightforward to verify that this framework can be extended to include active modes, which can be treated similarly to the PT or multimodal options. As future research directions, we aim to expand the framework by incorporating the attitude of users towards incentivization to refine the disutility functions, and testing the proposed strategy on a wider area with more PT lines and P&R facilities.

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