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RESEARCH

Modeling MobilityCoins—Charges, Incentives and Multi-period Budgets in Multimodal Transportation Networks

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Abstract
MobilityCoins are a tradable mobility credit (TMC) scheme variant. TMC schemes are a cap-and-trade scheme for managing mobility that are designed to limit negative externalities, e.g., congestion, of traffic. Next to having link-specific or origin–destination-specific charges for cars as in the common TMC scheme, the MobilityCoin scheme's distinctive elements are accommodating link-specific and origin-and-destination-specific charges and incentives for all modes of transport as well as being considered a mobility currency that can be earned, saved, and spent in multiple time periods. These distinctive features of the MobilityCoin scheme does not alter the core behavioral mechanism of TMC schemes of increasing car travel costs, but these features interfere with the credit market in terms of market volume and market price that ultimately affects traffic outcomes, e.g., an uncontrolled market volume increase can lower the market price that in turns increases the attractiveness of using the car. In this paper, we develop a mathematical model of multimodal macroscopic network flows and a MobilityCoin market to investigate the impacts of charges, incentives, and multi-period budgets. The model is implemented as a single-day model with an integration of sensitivity for multi-period budgets to study how the outcomes in the transportation system change with charges, incentives, and multi-period budgets. Further, we discuss implications for the policy design of MobilityCoins schemes.

Keywords Transport policy · Transportation network modeling · Tradable mobility credits · Road user charges

Introduction

It has been argued that "economists have had limited success in promoting economically efficient transportation and environmental externality policies" (Lindsey and Santos 2020). Around the world, arguably, the primary policies are fuel excise taxes and road user charges for toll roads, where only a few examples are frequently cited for their (partial) successes, e.g., London and Singapore (Leape 2006; Prud'homme and Bocarejo 20058; Metz 2018). Considering the urgent need "for deep CO2 mitigation in road transport" (Axsen et al. 2020), as well as the thread to the treasury from a decline in fuel excise tax revenue due to vehicle electrification, one of the essential overarching research questions in transport policy is what kind of schemes to implement instead?

In economics, a long discussion on "price vs. quantities" exists for regulating an economic system in terms of externalities, i.e., setting standards or limits or charging taxes (Weitzman 1974). Here, Dales was one of the first to propose such a quantitative instrument to manage external costs using a cap-and-trade scheme (Dales 1968). In transport, such policy instrument based on tradable mobility credits (TMC) has been put forward by Verhoef et al. (1997) to regulate externalities, but so far have not seen any real-world implementation, except first promising field experiments (Geng et al. 2023). Nevertheless, such a policy instrument has already seen implementation in the energy sector to, e.g., manage carbon emissions (Perroni and Rutherford 1993) and promote green energy deployment (Bergek and Jacobsson 2010; Frei et al. 2018).

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In transport, the cap-and-trade scheme usually works as follows: credits (or tokens, certificates, or permits) are required for traveling on a specific link, entering a specific area, or using certain infrastructures. The regulator defines an upper limit to the to-be-regulated quantity, e.g., emissions, congestion delays, or car travel, and issues credits to use parts of this overall quantity. Travelers obtain these credits from the regulator, e.g., free of charge or by auctioning, and redeem them for their mobility again at the regulator. Travelers can also sell their excess credits to travelers in shortage of credits, which generates additional monetary income for the seller. An overview of system designs is presented in Provoost et al. (2023), and aspects of the overall market design have been recently summarized comprehensively by Chen et al. (2023). As TMC market participants can negotiate and allocate the credits among themselves, a better performance compared to monetary fees can emerge in many circumstances (De Palma et al. 2018; De Palma and Lindsey 2020). Further, as credits can be initially distributed to market participants for free, participants not exceeding their initial allocation do not have to pay anything, which may support public acceptance of a TMC scheme (Krabbenborg et al. 2020).

Arguably, the seminal paper that re-initiated TMC research is Yang and Wang (2011), which provides the fundamental mathematical macroscopic model for a TMC scheme. Nevertheless, other modeling approaches have also been developed, e.g., an MFD-based approach in a multimodal context (Balzer and Leclercq 2022) or agent-based modeling approaches (Tian and Chiu 2015), where also the aspect of multi-period budgets has been included by (e.g., Miralinaghi and Peeta 2016). Further related to multi-period budgets are the within-day dynamics of a TMC scheme, which has been studied, e.g., by Seshadri et al. (2022), and the impact of day-to-day variability in demand and supply on the performance of a TMC scheme, which has been studied, e.g., by Lindsey et al. (2023). Research also studied user perceptions, the system's acceptance, and feasibility (Krabbenborg et al. 2020, 2021; Kockelman and Kalmanje 2005). Further, Servatius et al. (2023b) discussed how the ability and willingness to participate in TMC trading can be ensured; the authors conclude that it is feasible but challenging considering the complexity of interactions of parameters and interests. The idea of credits also extends to incentives, which can be collected and then exchanged for, e.g., money or public transport tickets (Hu et al. 2023), where Singapore's "Travel Smart Journeys"-scheme is presumably one of the most prominent schemes (Land Transport Authority 2023).

Recently, Bogenberger et al. (2021) proposed the TMC-scheme variant "MobilityCoins" that differs from a conventional TMC scheme in at least two aspects. First, it accommodates link-specific and origin-and-destination-specific charges and incentives for all modes of transport, not only cars, as in most variants present in the literature. Second, it is considered a currency in the mobility system that can be earned, saved, and spent. It has a natural validity spanning over multiple days or weeks, defined as multi-period budgets, compared to approaches in the literature that usually consider only one or a few days (Blum et al. 2022). These aspects interfere with the credit market and thus could affect the outcomes observed in the transportation system. For example, if too many credits are provided as incentives, the market price could drop, increasing the attractiveness of driving. Here, Schatzmann et al. (2023) recently showed using a stated-preference survey that the cost sensitivity for the credit price in the generalized travel cost depends on the time until the end of the validity period and the amount of budget left.

In this paper, we investigate how these multimodal incentives and multi-period budgets of a MobilityCoin scheme impact outcomes in the transportation system. We develop a mathematical model of static multimodal macroscopic network flows and of the MobilityCoin market that accommodates charges and incentives as well as considers the effects of multi-period budgets. We investigate the effects on transportation system outcomes of the interactions of charges, incentives, and multi-period budgets in a MobilityCoins scheme in a small transportation network and derive implications for policy design.

This paper is organized as follows. Section 2 presents the mathematical model, and Sect. 3 presents the case study network. Section 4 presents the results of the case study analysis before Sect. 5 ends with discussions and conclusions.

Mathematical model

Consider a transport network with $\mathcal{N}$ nodes, $\mathcal{A}$ arcs, and $\mathcal{M}$ modes of transport. Nodes are referenced by $i \in \mathcal{N}$ (with aliases j and k), arcs are a distinct pair of nodes and are referenced by the link start-end pair $(i,j) \in \mathcal{A}$, modes are referenced by $m \in \mathcal{M}$. In this model, three modes are considered: $\mathcal{M} \in \{\text{car, public transport, bicycle}\}$. Travelers are distinguished by their origin–destination pair $(o,d) \in \mathcal{OD}$. The set of origins and destinations is a subset of the set of nodes, i.e., $\mathcal{OD} \subseteq \mathcal{N}$. The overall demand d_{od} between origin o and destination d is assumed fixed and exogenous. The MobilityCoin system is characterized an initial allocation of credits γ to travelers, link-specific charges for the car mode κ_{ij} as only car travelers make route choice and origin–destination-specific charges λ_{odm} for all modes of transport. In this model, γ is assumed to be uniform. In case $\kappa_{ij} > 0$ or $\lambda_{odm} > 0$, the charge is subtracted from the available MobilityCoin budget; in case $\kappa_{ij} < 0$ or $\lambda_{odm} < 0$ the charge becomes a subsidy or incentive, i.e., it is added to the available budget. Here, the original MobilityCoin conceptualization argues that only sustainable modes of transport should be marginally subsidized as well as to limit the amount of MobilityCoins that can be earned to avoid induced travel only for such a purpose (Blum et al. 2022). Here, Xiao et al. (2019) argue that it should be ensured that "negative cycles", i.e., loops in the network with overall negative path costs should be avoided. This is not only because of induced travel but also because the minimum-cost path problem cannot be solved anymore. Hence, in the MobilityCoin system design, providing incentives should focus on λ_{odm} rather than κ_{ij} to ensure the nonexistence of negative cycles while limiting the overall amount of incentives provided to avoid induced travel.

In this macroscopic model, travelers make two choices. First, they choose their mode m. Second, all users choosing the car also choose their route. Mode choice and route choice are made based on the travel costs that comprise travel time costs and costs resulting from the charges $\kappa_{ij} > 0$ and $\lambda_{odm} > 0$. In this model, both choices are made simultaneously in such a way that the resulting travel costs across routes and modes lead to the stochastic user equilibrium (Daganzo and Sheffi 1977; Zhou et al. 2012), i.e., no traveler can improve her or his perceived travel costs by unilateral action. The stochastic user equilibrium relaxes the assumption of perfect knowledge of all travelers in the deterministic user equilibrium, i.e., Wardrop's first principle (Wardrop 1952). In the following, the mathematical model is explained step by step.

The presented multimodal extension is a generalization of the seminal mathematical formulation presented by Yang and Wang (2011) and continuous the multimodal work of (Servatius et al. 2023a). The mathematical model describes a macroscopic traffic assignment and uses built-in parameters to simulate the impact of multi-period budgets. The model defined in the following is formulated as a mixed-complementarity problem (MCP) (Ferris et al. 1999) and is implemented in GAMS (GAMS Development Corporation 2018). The model's variables and parameters are summarized in Table 1.

This demand is distributed across modes using a logit-based assignment. As shown in Eq. 1, the choice of modes depends on the minimum travel costs W_{odm} between o and d using mode m and a scale parameter μ.

$$X_{odm} = \frac{\exp\left(-\mu W_{odm}\right)}{\sum_{m' \in \mathcal{M}} \exp\left(-\mu W_{odm'}\right)} \tag{1}$$

In this mathematical model, the costs for MobilityCoins enter the travel costs of all modes through link-specific and origin-and-destination-specific charges and incentives, each multiplied by the MobilityCoin market price P. The MobilityCoin system is characterized by multi-period budgets which means that MobilityCoins can be earned, saved, and spent at and over various different days throughout a certain validity period. To describe such multi-period budget behavior, consider parameters b and t that describe

Table 1 Variables and parameters in the model

Symbol	Explanation
P	Tradable mobility credit market price
X_{odm}	Share of travelers using the car on origin–destination pair (o, d)
T_{ij}	Travel time on link (i, j)
C_{ij}	Perceived travel cost on link (i, j)
Q_{ij}	Flow on link (i, j)
Y_{ijk}	Partial flow on link (i, j) towards k
W_{odm}	Minimum perceived travel costs from origin–destination (o, d) using mode m
M_{ijm}	Minimum perceived travel costs between i and j
ζ	Random component to represent travelers' perception error with $E(\zeta_{ij}) = 0$
μ	Mode choice scale parameter
γ	Initially issued credits per traveler
λ_{odm}	Origin–destination-specific MobilityCoins charges
κ_{ij}	Link-specific MobilityCoins charges
τ_{odm}	Free-flow travel time between origin o and destination d using mode m
b	MobilityCoin budget status parameter with $b \in [0;1]$
t	MobilityCoin time period parameter with $t \in [0;1]$
η	MobilityCoin cost sensitivity
t_{ij}^{0}	Free-flow travel time on link i-j
c_{ij}	Capacity on link i-j
β	BPR function parameter
n	BPR function parameter

the budget status and the time until the end of the validity period, respectively. In this mathematical model, we follow the findings as reported by Schatzmann et al. (2023). Cost sensitivity increases with fewer MobilityCoins available in the budget, but there is an interaction effect between the number of MobilityCoins left and the number of days until the end of the validity period: with the same number of MobilityCoins left, the cost sensitivity is higher with more days left until the end of the validity period. We integrate these findings as follows. Consider that both parameters have values between zero and one and that budget status b is equal to one if all MobilityCoins are available and zero if none are available anymore; t is equal to one at the start of the validity period and is zero at the end of the validity period. We approximate this for the cost sensitivity η as shown in Eq. 2.

$$\eta = t(1 - b) \tag{2}$$

By approximation, we mean using the relationships reported by Schatzmann et al. (2023) and integrating them into the simplest functional form with interaction effect as defined in Eq. 2 because no further information is currently available on the behavioral model. Note that a better behavioral model can replace this functional relationship once data for this is available. It is important to mention that Schatzmann et al. (2023) obtained these findings not at the interval boundaries but around the midpoint of each interval. Consequently, the relationship in Eq. 2 is only meaningful around the midpoint values

Figure 1 illustrates the cost sensitivity for different parameter values of b and t. If the MobilityCoin budget is almost fully available, i.e., b is large, η becomes small, while it gets smaller the shorter the time period until the end of the validity period given the same available MobilityCoin budget. Importantly, in this model, the feature of multi-period budgets are only considered in the cost sensitivity η, but not in the market clearing condition.

In this mathematical model, the MobilityCoin charges with their respective cost sensitivity enter the resulting stochastic user equilibrium travel costs W_{odm} as given in Eq. 3. The origin-and-destination charges λ_{odm} weighted by the product of the MobilityCoin cost sensitivity η and the MobilityCoin market price P is added to the minimum travel costs M_{odm} for each mode. Parameter λ_{odm} can accommodate incentives, e.g., for cycling, but also charges for cars, e.g., for parking.

$$W_{odm} = M_{odm} + \eta P \cdot \lambda_{odm} \tag{3}$$

In this model, we consider that only cars experience congestion effects and have link-specific charges κ, while public transport and bicycles have fixed travel times on their respective origin-and-destination pair. Thus, we conveniently set for public transport and bicycles $M_{odm} \equiv \tau_{odm}$, where τ_{odm} is the free-flow travel time between origin o and destination d.

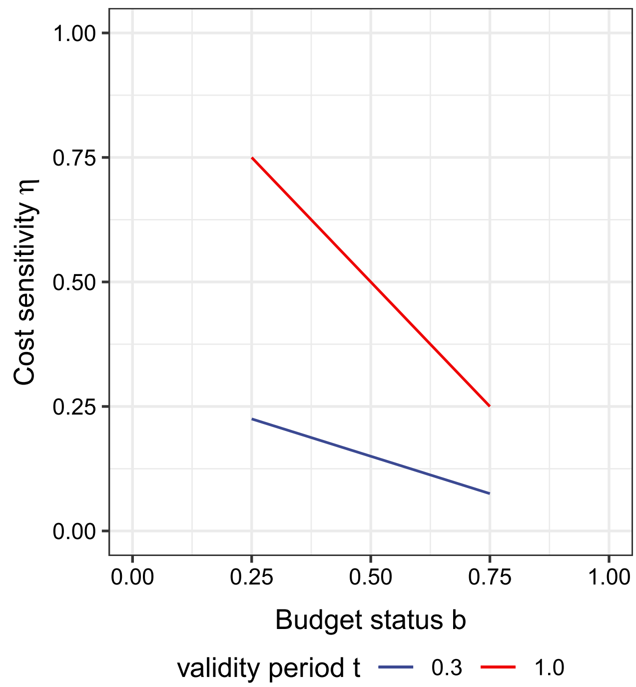

Fig. 1 MobilityCoin cost sensitivity as a function of budget depletion b and time until the end of the validity period t

Thus, only $M_{od,car}$ has to be computed from the stochastic user equilibrium flow pattern in the network.

The minimum travel costs $M_{od,car}$ are obtained as follows. Consider that the car travel costs C_{ij} on link i-j comprises two elements. First, the travel time T_{ij}. The link travel time is defined in Eq. 4 and follows the Bureau-of-Public-Roads (BPR) function (Bureau of Public Roads 1964) with the usual parameters and is a function of link flow Q_{ij}.

$$T_{ij} = t_{ij}^0 \left(1 + \beta \left(\frac{Q_{ij}}{c_{ij}} \right)^n \right) \tag{4}$$

The second element is the MobilityCoin link charge κ_{ij} valued at MobilityCoin market price P weighted by the cost sensitivity β. As aforementioned, both elements, the travel time costs as well as the MobilityCoin link charges, constitute the perceived link travel costs for car travelers C_{ij} as defined in Eq. 5. Here, ζ_{ij} is the corresponding random component (Zhou et al. 2012).

$$C_{ij} = T_{ij} + \eta P \cdot \kappa_{ij} + \zeta_{ij} \tag{5}$$

The arbitrage condition for car drivers to use link (i, j) follows a stochastic user equilibrium (Daganzo and Sheffi 1977) that relaxes the assumption of perfect knowledge of all travelers in the deterministic user equilibrium or Wardrop's first principle (Wardrop 1952). It is formulated in this model as given in Eq. 6 based on Van Nieuwkoop et al. (2016), but modified using the perceived link travel costs C_{ij}. Y_{ijk} are

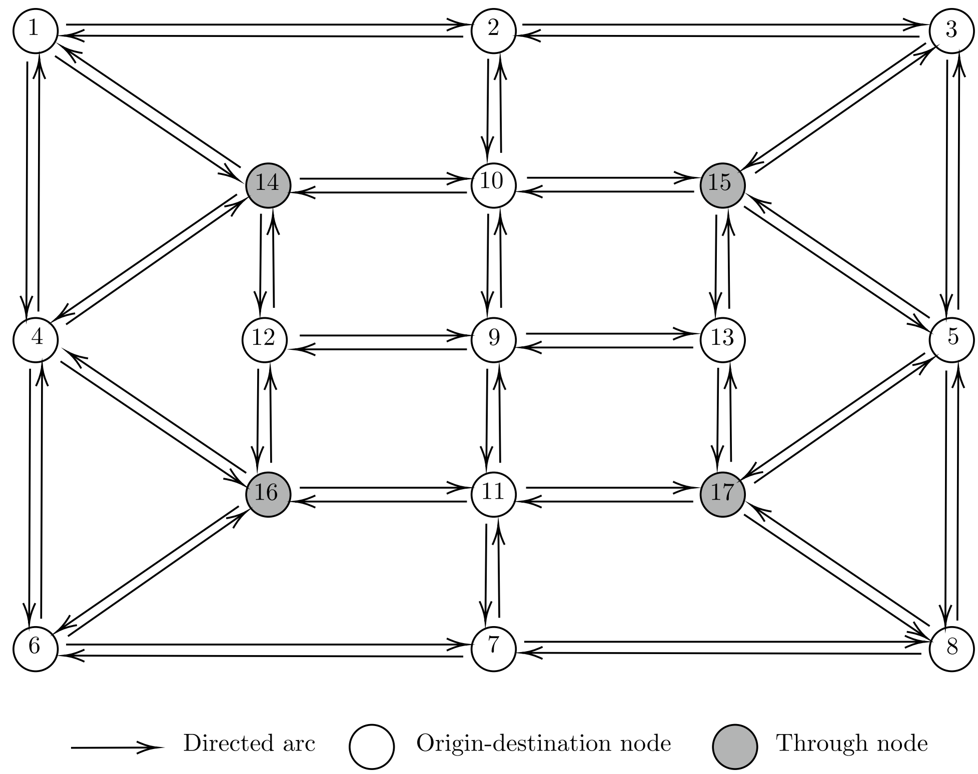

Fig. 2 Case study network

the partial flows on that link towards k. When the minimum perceived travel costs from node i to k over j equal the minimum perceived travel costs from node i to k, the link is used for car drivers towards k. In other words, Eq. 6 considers the perceived travel costs from i to k, i.e., origin and destination, while exploring route alternatives connected to node i over j. It is from this Equation from which $M_{od,car}$ can be derived.

$$C_{ij} + M_{jk,car} \geq M_{ik,car} \quad \perp \quad Y_{ijk} \geq 0 \tag{6}$$

The partial link flows Y_{ijk} can then be aggregated to link flows Q_{ij} as the sum over all partial flows along those links as defined in Eq. 7.

$$Q_{ij} = \sum_{k} Y_{ijk} \tag{7}$$

In the model, it must be ensured that the inflows and outflows at each node in the network are balanced. This is ensured by Eq. 8.

$$d_{od} X_{od\text{car}} = \sum_{(o,j)\in\mathcal{A}} Y_{ojd} - \sum_{(j,o)\in\mathcal{A}} Y_{jod} \tag{8}$$

Last, as the MobilityCoins scheme is a market-based system, Eq. 9 resembles the market clearing condition. Here γ is amount of credits initially issued per traveler. In other words, the left-hand side of Eq. 9 results into the total market volume of MobilityCoins. κ_{ij} is the MobilityCoins link charge for car travelers and λ_{odm} is a origin–destination mode-specific charge for all other travelers. The complementarity conditions ensure that the MobilityCoins market price P is only non-zero when supply and demand are balanced. If the market is over-supplied, the market price would be consequently zero.

$$\gamma \cdot \sum_{(o,d)\in\mathcal{OD}} d_{od} \geq \sum_{(i,j)\in\mathcal{A}} \kappa_{ij} Q_{ij} + \sum_{(o,d,m)\in\mathcal{OD}} \lambda_{odm} * d_{od} * X_{odm} \quad \perp \quad P \geq 0 \tag{9}$$

In conclusion, the presented mathematical model is a single-day model with an integration of sensitivity for multi-period budgets. Hence, this model cannot be used to simulate and study the actual performance of a TMC or MobilityCoin system over time during a validity period, but rather to study how the average outcomes in the transportation system change when pivoting slightly the cost sensitivity as a consequence of changes in the available budget or time until the end of the validity period.

Case study definition

The objective of a MobilityCoin scheme is to reduce the external cost of car travel (Blum et al. 2022), which typically includes congestion externalities as well as pollution, noise, etc. It is the agency that defines γ, κ_{ij}, and λ_{odm} in such a way that the targets in terms of reduction in external costs are achieved. In doing so, the agency can weigh which external costs to prioritize over others. In this case study, the simple policy objective of reducing overall car travel is assumed because it is generally associated the most with external costs. This can lead to counter-intuitive outcomes that total travel time increases as the travel costs of faster modes, i.e., the car, are not competitive anymore. To illustrate the primary transport and economic mechanisms of a MobilityCoin scheme following the assumed policy objective, we apply the model developed in Sect. 2 to the simple network shown in Fig. 2. It is important to note that the presented model does not capture the effects of transaction costs of credits between parties (e.g., Nie 2012) and the effects of income (e.g., Krabbenborg et al. 2020), but both can be relevant in the performance and success of TMC schemes.

The network has 17 nodes of which 13 are origin and destination nodes and four are through nodes, i.e., the demand entering or exiting the network at these nodes is 0. The network has directed arcs as shown in Fig. 2. In the network, three modes of transport operate: cars, public transport, and bicycles, where only cars experience congestion effects. It is assumed that the same technology and infrastructure, i.e., level of service, for bicycles and public transport, is available in the entire network, irrespective of whether being in the CBD or not. For example, the same strategy of providing dedicated bus lanes or priority at signals.

This network is centered around node “9”, while having symmetry with the line from nodes “2”, “10”, “9”, “11”, “7”; hence we consider the area defined by all six mentioned nodes as the “CBD” (central business district) area of the network with all links between these six nodes belonging to the “CBD”. Table 3 shows the parameters for the volume-delay function of each link.

We generate a random origin–destination matrix that is provided in Table 4. There is sufficient travel demand in the network to lead to congestion effects considering the link parameters shown in Table 3. We define the origin–destination travel times τ_{odm} for public transport and bicycles as follows. First, we calculate the car free-flow travel times in the network shown in Fig. 2. Second, we set the public transport travel times $\tau_{od,\mathrm{pt}}$ on each origin–destination pair and the bicycle travel times $\tau_{od,\mathrm{bicycle}}$ to a multiple of the car free-flow travel times, which is randomly sampled from a uniform distribution between 1.35 and 1.45 for public transport and between 1.40 and 1.50 for bicycles. Tables 6 and 5 provide the resulting travel times.

In this case study analysis, the status-quo scenario is defined by having no MobilityCoin system in place, i.e., the MobilityCoin market price is set to zero or $P \equiv 0$. When implementing the MobilityCoin scheme, the following five policy design and system status parameters affect the transportation system outcomes and, thus, factor into the efficiency and success of the MobilityCoin system implementation.

- The initial allocation of credits γ: all else being equal, an increasing γ leads to an increase in market volume, decreasing the market price and thus decreasing the generalized travel costs for the car, making it more attractive.
- The link-specific charges and incentives κ_{ij} for cars: all else being equal, increasing κ_{ij} increases the generalized travel costs for cars, making it less attractive. However, considering the limited market volume of MobilityCoins, κ_{ij} also determines the maximum car travel in the network. In case of $\kappa_{ij} < 0$, i.e., it becomes an incentive; it increases the total supply of MobilityCoins and reduces the MobilityCoin market price, thus the general travel cost, making the car more attractive. If this incentive is unconditional and unrestricted, an upper limit to car travel is not given anymore.
- The origin-and-destination charges and incentives λ_{odm}: all else being equal, an increasing λ_{odm} increases the MobilityCoin market price and thus the generalized travel costs. In the case of $\lambda_{odm} < 0$, it becomes an incen-

Table 2 Trips and travel time in the status-quo scenario

General statistics		
Total number of trips		306,837
Total travel time (10e6 min)		9.45
Total travel distance by car (10e6 km)		26.26
Modal share		
Mode of transport	By number of trips	By travel time
Car	33.2%	67.8%
Public transport	33.4%	15.8%
Bicycle	33.4%	16.4%

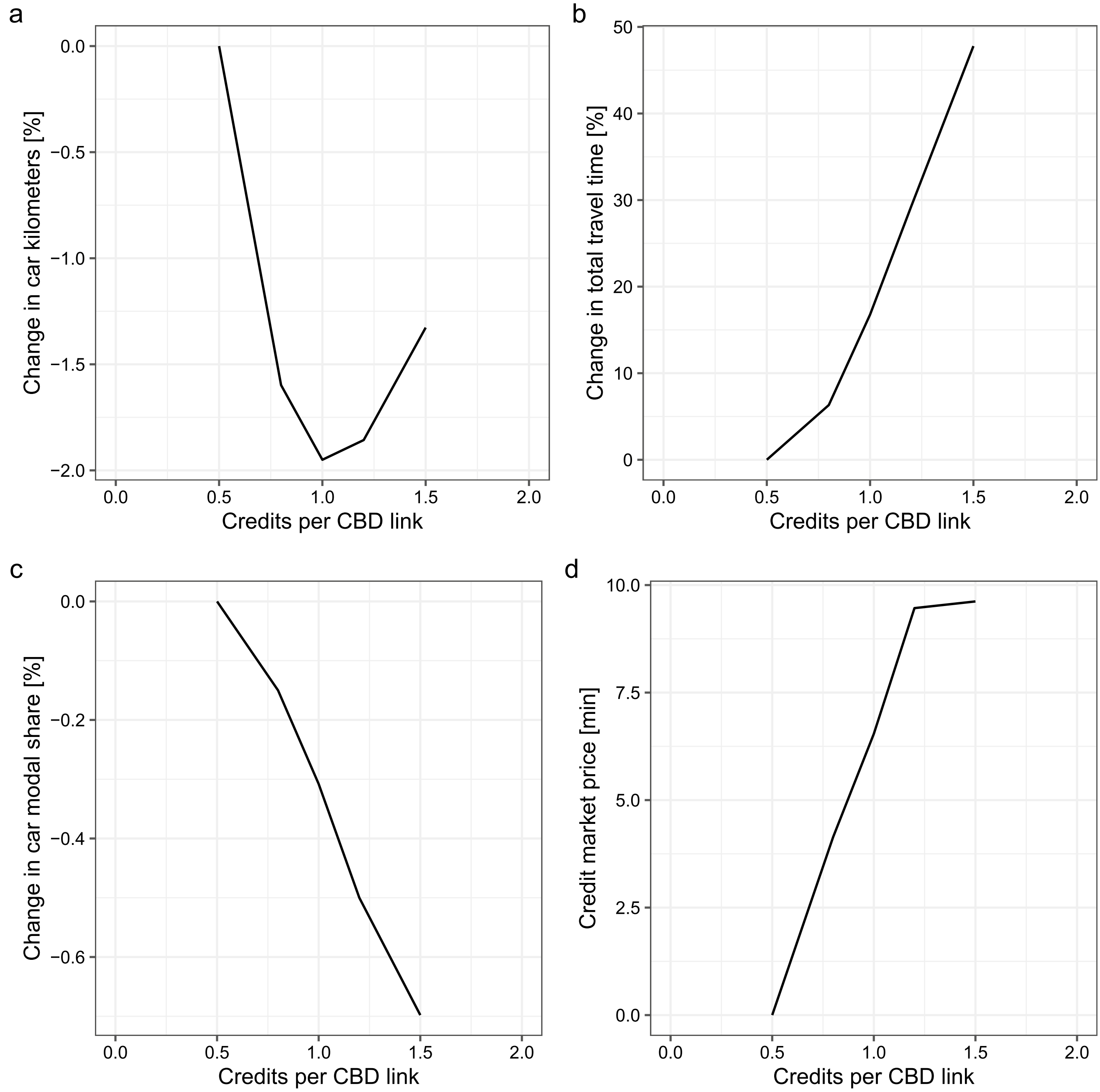

Fig. 3 Changes in system outcomes with link-specific charges for car drivers in the core of the network compared to the status quo outcomes

tive; it increases the total MobilityCoin market volume and decreases the MobilityCoin market price, hence reducing the generalized travel costs, eventually making the car more attractive.

- The multi-period budget indicators of budget status *b* and time until the end of the validity period *t*: all else being equal, the less budget is available, i.e., *b* decreases, and the longer the time period until the end of the MobilityCoin validity period, i.e., *t* increase, travelers become more cost sensitive for MobilityCoin charges, i.e., their perceived generalized travel costs increase for modes with $\lambda_{odm} > 0$ or $\kappa_{ij} > 0$, or decreases for modes with $\lambda_{odm} < 0$ or $\kappa_{ij} < 0$.

It can be seen that these five parameters of policy design and system status parameters strongly interact and affect the outcomes in the transportation system, eventually interfering with the intended policy targets of the MobilityCoin system. We measure the outcomes in the transportation system using

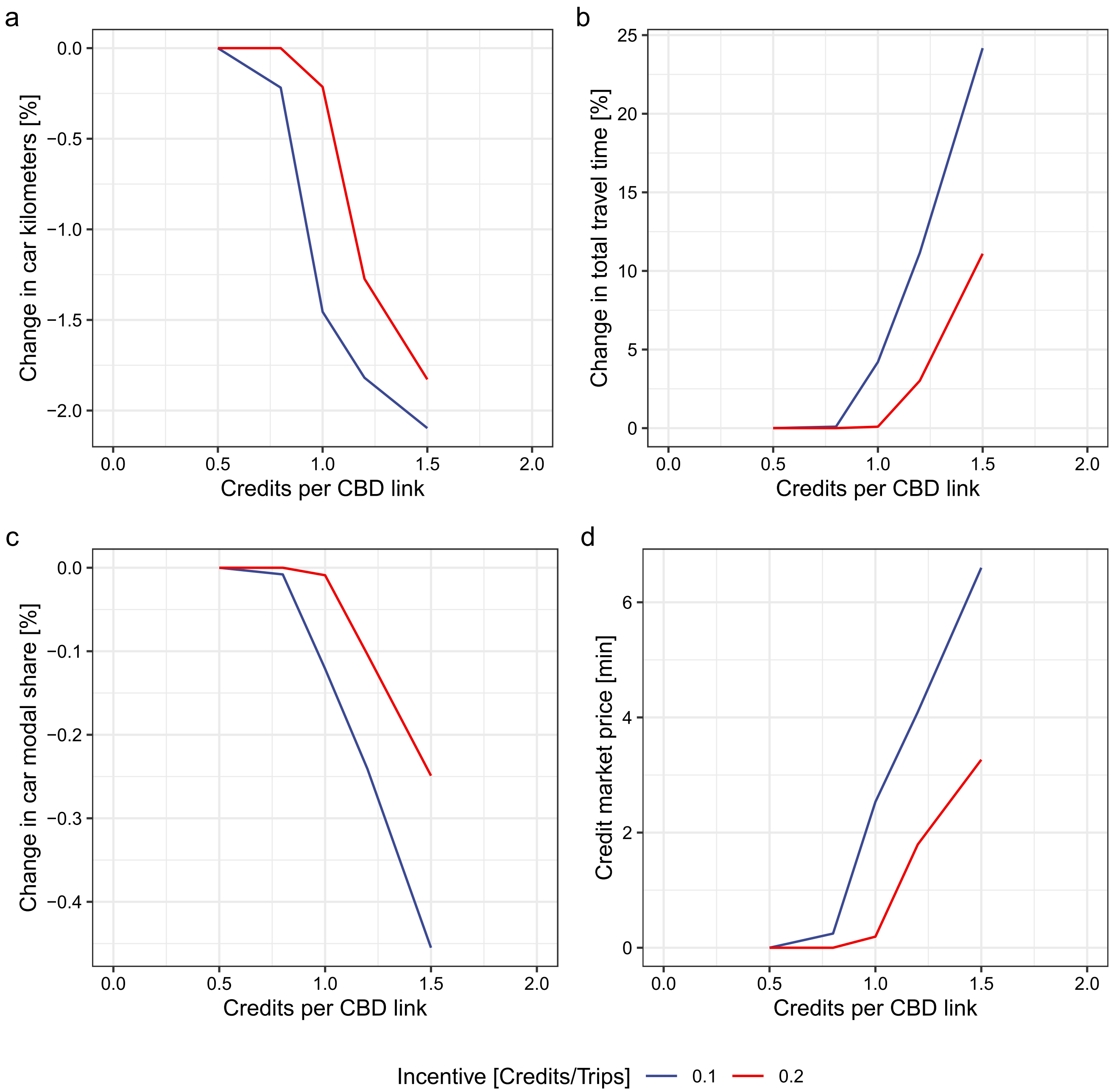

Fig. 4 Changes in system outcomes with incentives for cyclists and link-specific charges for car drivers in the core of the network compared to the status quo outcomes

- The number of trips per mode and their shares,
- The total distance traveled by the car mode as it is the primary source of externalities, which are likely to be regulated by a tradable credit scheme,
- The total travel time by mode and their shares
- The MobilityCoin market price.

In the case study, we intentionally exaggerate the selected policy design and system status parameters or their ranges to highlight the effects of these on the transportation system outcomes: we set $\gamma = 0.1$ MobilityCoins per traveler and $\kappa_{ij,car} \in \{0.5;0.8;1;1.2;1.5\}$ MobilityCoins per link for all "CBD" links and to zero for all other links. When introducing, we set the origin–destination specific charges to $\lambda_{od,bicycle} \in \{-0.1; -0.2\}$, where the minus sign indicates that it is a subsidy or incentive compared to a charge that has a positive sign. When considering the multi-period budgets, we set $t \in \{0, 0.3, 0.8\}$ and $t \in \{0.3, 0.8, 1\}$. Further, we set the scale parameter for the mode choice to $\mu = 0.001$.

In the following section, we investigate the system outcomes with increasing complexity from the status quo with no tradable credit scheme (see Sect. 4.1), a MobilityCoin system only with link-specific charges for cars, i.e., a common tradable credit scheme, in Sect. 4.2, a MobilityCoin system with link-specific charges for cars and incentives for bicycles in Sect. 4.3, and a MobilityCoin system with link-specific charges for cars, incentives for bicycles, and considering multi-period budgets in Sect. 4.4.

Case Study Investigation

In this section, we use the mathematical model from Sect. 2 to investigate and discuss the system outcomes with the increasing complexity of adding policy design and system status parameters of that model. First, we present the status quo or the benchmark without any MobilityCoins of the case study presented in Sect. 3. Second, we introduce link-specific MobilityCoin charges for cars on the "CBD" links (see Fig. 2), which is similar to a common tradable credit scheme. Third, we additionally introduce incentives, i.e., negative charges, for cyclists. Fourth, we add to the previous car charges and bicycle incentives the aspect of multi-period budgets.

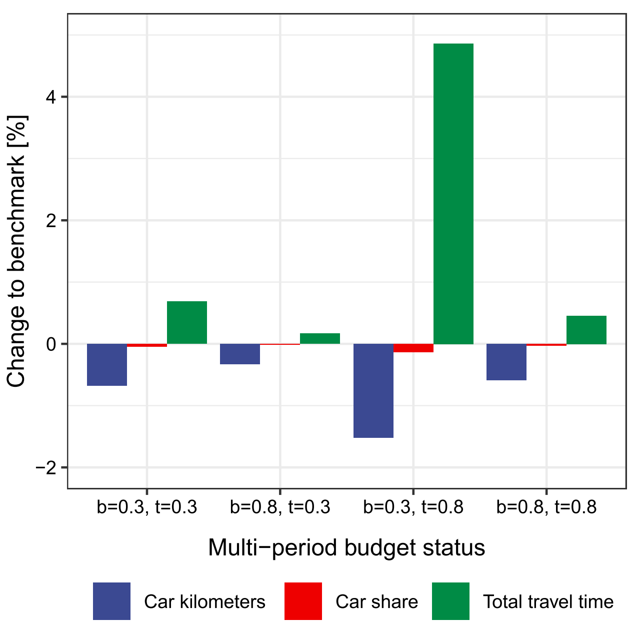

Fig. 5 Investigation of the multi-period aspect in transportation system outcomes compared to the status quo. The market clearing with parameters $\kappa_{ij,car} = 1.5$ and $\lambda_{od,bicycle} = -0.1$ is assumed and fixed. MobilityCoin budget status b (greater means more MobilityCoins are available) and time until the end of the MobilityCoin period t (greater means more time until the end of the validity period)

Status Quo

Table 2 summarizes the transportation system outcomes for the status quo scenario defined in Sect. 3. Overall, more than 300,000 travelers are navigating the multimodal network. These travelers distribute almost equally to all three modes. This is intuitive as it can be expected that the car is chosen by travelers until travel costs similar to public transport and bicycles result. Considering the modal share by travel time, it can be observed that those taking the car in the network have substantially larger travel times compared to public transport and bicycle users.

MobilityCoins only with Link-specific Charges for Cars

In Fig. 3 we show the outcomes in the case study transportation system when a MobilityCoin scheme with only link-specific charges on all links connecting to node "9" are introduced. Here, as already mentioned, we set the initially allocated budget to $\gamma = 0.1$ MobilityCoins per traveler and the link-specific charge to $\kappa_{ij,car} \in \{0.5;0.8;1;1.2;1.5\}$ MobilityCoins per link. Note by simulating different link charges $\kappa_{ij,car}$ we investigate the sensitivity of the outcomes. Generally, we find in Fig. 3 that for $\kappa_{ij,car} = 0.5$ no impact compared to the status quo is observed. In other words, the number of initially allocated MobilityCoins exceeds the number of MobilityCoins required by all car travelers navigating the links in the center of the network. When we then increase the charge, we observe the expected pattern, namely that car travel declines and the MobilityCoin market price increases. Here, the market price is expressed in time units as in the case study model, all cost elements are expressed in time. For example, a MobilityCoin market price as seen in Fig. 3d of 5 min per MobilityCoin means that for link charge of one MobilityCoin per link, the travel costs increase by 5 min, which is a multiple of the free-flow speed (see also Table 3). Hence, travel on these links becomes highly unattractive. With car users following the equilibrium principle, drivers distribute to other routes until an equilibrium is reached. This explains the substantial increase in car travel distance seen in Fig. 3a and total travel time seen in Fig. 3b when increasing the charges from $\kappa_{ij,car} = 0.5$ to $\kappa_{ij,car} = 1.5$. Arguably, the desired effect of introducing a TMC-scheme seems fading, which is also emphasized by the fact that no further market price increase is seen in Fig. 3b, suggesting that the shifting potential has been almost fully exploited.

MobilityCoins with Charges and Incentives

The additional introduction of incentives for cyclists to the case study network with only link-specific charges means that the total market volume of MobilityCoins will increase. Consequently, it can be expected that the observed effects in Fig. 3 are attenuated. Investigating with $\lambda_{od,bicycle} \in \{-0.1; -0.2\}$ per bicycle trip, i.e., an incentive of 0.1 and 0.2, respectively, we find exactly this attenuation as seen in Fig. 4. Here, we also see that with increasing incentives, the attenuation is stronger: we find that at $\lambda_{od,bicycle} = -0.1$ the MobilityCoin market is inactive at $\kappa_{ij,car} = 0.5$, while it stays inactive until $\kappa_{ij,car} = 0.8$ when $\lambda_{od,bicycle} = -0.2$. The MobilityCoin market price also does not reach the levels of the link-charges-only scenario from Fig. 3, leading to a less substantial shift to other modes and routes, in particular, is the rebound in car travel as seen in Fig. 3a not observed anymore.

MobilityCoins with Charges, Incentives, and Multi-period Budgets

In the analysis of the impact of multi-period budgets, we assume the market clearing with parameters $\kappa_{ij,car} = 1.5$ and $\lambda_{od,bicycle} = -0.1$ from Fig. 4, leading to $P = 3.26$ min. In other words, for this investigation, the market is considered fixed to investigate the impact of budget status b (greater b means more MobilityCoins are available) and time until the end of the validity period t (greater t means more time until the end of the validity period is available).

In Fig. 5 we show the results of this investigation. First, it can be seen that different parameter combinations of b and t impact the transportation system outcomes compared to the status quo differently. Nevertheless, the changes in car kilometers, car share and total travel time are all in the same direction as observed before. Generally, the results are intuitive: we find that the strongest impact occurs when much time is left until the end of the validity period, but not much is left of the available budget ($b = 0.3, t = 0.8$); contrary, the smallest impact is found when much of the budget is available and the time until the end of the validity period is short ($b = 0.8, t = 0.3$).

Synthesis

The presented investigation emphasizes the complex interactions of charges, incentives, and multi-period budgets with respect to the outcomes of a multimodal transportation system. The presented case study is a simple network with exaggerated parameters to clearly point out what could happen and what should be considered in the policy design to avoid, e.g., the market is becoming inactive, or the market outcomes support substantial car detours, likely thwarting the objective of reducing overall car travel. As travel demand is distributed in the network according to the well-known Wardrop equilibrium principle, it is thus not trivial to optimize single policy parameters of a MobilityCoin or TMC scheme as the entire transportation system response in the equilibrium must be evaluated and considered for the decision making.

Discussion and Conclusions

In this paper, we introduced a mathematical model to study the impact of charges, incentives, and multi-period budgets in a MobilityCoin scheme, a variant of tradable mobility credits. The model was implemented as a single-day model with an integration of sensitivity for multi-period budgets to study how the outcomes in the transportation system change with charges, incentives, and multi-period budgets. We applied the introduced model to a simple multimodal case study network to illustrate transportation system outcomes under different design configurations. We have shown that the different aspects of the MobilityCoin scheme (charges, incentives, and multi-period budgets) interfere strongly with the outcomes compared to the status quo. Although all system implementations proved the capability of achieving the targeted reduction in car travel, it became apparent that it is likely not trivial to set policy parameters in such a way that the desired targets, e.g., emission or congestion levels, result. Here, using a mathematical program with equilibrium constraints (MPEC) could be a starting point (e.g., Ferris et al. 2005). Nevertheless, the aspect of heterogeneity in travelers' preferences as well as the possibility for a more heterogenous initial allocation of MobilityCoins or credits must be considered too for the policy design of a MobilityCoin scheme.

In closing, tradable mobility credits or MobilityCoins are an alternative to price-based instruments like congestion charges or parking fees. With these instruments becoming more and more unpopular in public and politics, their implementation and thus ability to optimize the performance of the transportation system is likely to subside. Consequently, despite the complexity and challenges of a real-world implementation of a MobilityCoin scheme, investigating such a scheme further is promising, in particular as its feature of providing incentives and providing travelers the opportunity to trade in credits or travel time for additional monetary income, might support its introduction and ability to optimize the outcomes of the transportation system. Here, it should also be mentioned that such a tradable mobility credit scheme could also be seen as a novel opportunity to design and operate transportation systems that support agglomeration effects (Graham 2007; Loder et al. 2021).

Table 3 Parameters of the network links shown in Fig. 2

i	j	length [m]	t_{ij}^0 [s]	β [s]	n [-]	c_{ij} [veh/h]
1	2	3000	240	0.15	4	1974
2	1	3000	240	0.15	4	2030
2	3	2900	232	0.15	4	1991
3	2	2900	232	0.15	4	2037
1	4	3100	248	0.15	4	2009
4	1	3100	248	0.15	4	2059
4	6	3000	240	0.15	4	2070
6	4	3000	240	0.15	4	1969
6	7	2900	232	0.15	4	2029
7	6	2900	232	0.15	4	1947
7	8	3100	248	0.15	4	1908
8	7	3100	248	0.15	4	1993
5	8	2900	232	0.15	4	1989
8	5	3100	248	0.15	4	2004
5	3	3000	240	0.15	4	1909
3	5	2900	232	0.15	4	1983
1	14	183	14.64	0.15	4	1731
14	1	255	20.4	0.15	4	1773
4	14	235	18.8	0.15	4	1879
14	4	279	22.32	0.15	4	1857
4	16	108	8.64	0.15	4	1876
16	6	187	14.96	0.15	4	1869
14	12	206	16.48	0.15	4	1783
12	14	113	9.04	0.15	4	1700
12	16	177	14.16	0.15	4	1899
16	12	218	17.44	0.15	4	1835
14	10	288	23.04	0.15	4	1892
10	14	218	17.44	0.15	4	1797
2	10	1498	98.05	0.15	4	4171
10	2	1501	98.25	0.15	4	3996
10	9	1474	96.48	0.15	4	4000
9	10	1519	99.43	0.15	4	3897
12	9	1550	101.45	0.15	4	3823
9	12	1462	95.70	0.15	4	4107
16	11	157	12.56	0.15	4	1713
11	16	176	14.08	0.15	4	1820
7	11	1487	97.33	0.15	4	3928
11	7	1512	98.97	0.15	4	3804
9	11	1504	98.44	0.15	4	3946
11	9	1550	101.45	0.15	4	3913
9	13	1455	95.24	0.15	4	4083
13	9	1549	101.39	0.15	4	3808
11	17	273	21.84	0.15	4	1862
17	11	143	11.44	0.15	4	1827
13	17	177	14.16	0.15	4	1776
17	13	252	20.16	0.15	4	1749
10	15	262	20.96	0.15	4	1814
15	10	238	19.04	0.15	4	1715
13	15	173	13.84	0.15	4	1875
15	13	251	20.08	0.15	4	1783
15	3	284	22.72	0.15	4	1720

Table 3 (continued)

i	j	length [m]	t_{ij}^0 [s]	β [s]	n [-]	c_{ij} [veh/h]
3	15	183	14.64	0.15	4	1878
15	5	273	21.84	0.15	4	1865
5	15	240	19.2	0.15	4	1710
17	5	265	21.2	0.15	4	1871
5	17	243	19.44	0.15	4	1881
17	8	216	17.28	0.15	4	1847
8	17	260	20.8	0.15	4	1789

Table 4 Origin and destination table for the case study

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	0	1860	1404	2550	1506	2448	1104	1794	2754	1245	1740	1827	2490	0	0	0	0
2	1149	0	2406	2019	2346	918	1746	960	2034	2694	2430	2298	2145	0	0	0	0
3	1815	1743	0	2781	1365	2802	2832	1008	2556	1743	2370	2880	1194	0	0	0	0
4	2496	2250	1416	0	1743	2193	1050	2973	1989	2715	1170	1968	1761	0	0	0	0
5	1884	2601	2430	1830	0	2328	2433	2352	2088	1965	2109	2055	1293	0	0	0	0
6	2274	906	2553	2058	1038	0	1755	2160	2979	2088	987	2544	2451	0	0	0	0
7	2526	1248	1326	2643	1293	2193	0	1149	1671	2871	2943	993	1257	0	0	0	0
8	1110	2436	2565	1560	1515	2271	2364	0	1083	2028	2307	2934	1776	0	0	0	0
9	972	1530	1422	1479	1002	1557	2103	1494	0	951	2397	1401	1026	0	0	0	0
10	1953	1224	2091	2781	1212	2166	1203	2940	2448	0	1890	966	2730	0	0	0	0
11	1845	2094	1983	2271	1821	1446	2301	2691	2937	2283	0	2391	2631	0	0	0	0
12	1872	1653	2313	2121	1998	2700	2529	1608	2145	2973	1965	0	2484	0	0	0	0
13	1209	1371	1824	1578	2760	2271	1689	1371	1287	1869	2715	2997	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The unit is number of travelers

Table 5 Origin–destination travel times in seconds for bicycles in the network

		Origin												
		1	2	3	4	5	6	7	8	9	10	11	12	13
Destination	1		200	100	57	111	391	230	138	175	56	87	44	103
	2	201		187	198	196	546	382	251	282	142	228	183	194
	3	115	200		124	63	477	259	109	195	62	117	110	53
	4	53	200	103		115	350	234	138	188	58	89	45	102
	5	118	208	51	92		427	198	59	194	61	64	104	52
	6	89	233	133	35	85		189	90	177	94	42	41	80
	7	229	374	233	175	195	344		186	285	224	139	185	183
	8	145	239	93	87	54	448	201		178	104	56	98	45
	9	186	283	185	179	187	526	298	190		138	146	151	145
	10	53	142	50	62	56	403	239	109	142		92	48	47
	11	81	238	86	30	44	379	142	48	142	88		40	37
	12	45	187	99	37	93	374	189	94	137	50	44		82
	13	111	197	50	94	59	448	205	60	135	60	62	99	

Table 6 Origin–destination travel times in seconds for public transport in the network

		Origin												
		1	2	3	4	5	6	7	8	9	10	11	12	13
Destination	1		197	101	55	109	379	216	127	170	52	83	41	102
	2	186		189	199	188	520	374	235	281	142	225	184	180
	3	117	202		121	59	457	244	107	179	61	109	107	50
	4	52	188	101		111	342	229	131	179	54	86	44	99
	5	111	199	52	90		416	194	58	177	59	59	95	49
	6	83	220	128	33	85		172	89	169	87	41	41	77
	7	215	354	220	164	179	314		190	274	220	139	176	177
	8	134	242	90	83	50	423	194		178	105	53	90	43
	9	190	271	182	166	180	512	270	185		132	145	147	138
	10	51	136	46	58	54	391	221	102	140		92	44	46
	11	81	220	87	29	43	362	131	46	135	84		38	35
	12	45	180	93	37	84	366	177	89	133	46	44		81
	13	111	190	48	89	56	417	195	59	131	57	59	98	

Appendix A. Case study network parameters

See Tables 3, 4, 5 and 6.

Author Contributions K.B. conceived the presented idea. A.L. developed the mathematical model, performed the formal analysis and computations. A.L. and K.B. interpreted the results. A.L. and K.B. wrote the manuscript.

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Declarations

Conflict of Interest The authors have no Conflict of interest to declare.

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