

Optimizing the geometry of transportation networks in the presence of congestion

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Urban transport systems are gaining in importance, as an increasing share of the global population lives in cities and mobility-based carbon emissions must be reduced to mitigate climate change and improve air quality and citizens' health. As a result, public transport systems are prone to congestion, raising the question of how to optimize them to cope with this challenge. In this paper, we analyze the optimal design of urban transport networks to minimize the average travel time in monocentric as well as in polycentric cities. We suggest an elementary model for congestion and introduce a numerical method to determine the optimal shape among a set of predefined geometries considering different models for the behavior of individual travelers. We map out the optimal shape of fundamental network geometries with a focus on the impact of congestion.

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I. INTRODUCTION

The structure and design of optimal transportation networks plays an important role throughout different disciplines, ranging from biological systems [1–3] to man-made networks such as hydraulic networks [4,5], power grids [6], and urban transportation systems [7,8]. The design of a transportation network is governed by the task it is supposed to perform, e.g., minimizing the dissipated power in electric networks, minimizing the cost to build the network or minimizing the averaged travel time.

Real-world supply and transportation networks display a variety of shapes depending on their history, their task, and their surroundings [9–11]. For example, in the case of urban transport systems, the design of the network may depend on the city size and the degree to which cities are historically grown or centrally planned [12]. Although most of them have grown over decades and were built in several small steps, one observes several patterns which occur frequently in various cities and have been analyzed using different topological indicators [13–16]. Building an efficient urban transportation network becomes increasingly important to reduce individual traffic which leads to congestion, high emission of green house gases [17] and adverse effects on air quality and citizens' health [18].

Congestion is a central topic in traffic research and planning. Empiric and numerical studies of road traffic show how vehicle velocities decrease with density up to a complete traffic jam, which is commonly summarized in the fundamental diagram of traffic flow [19,20]. Methods to manage or optimize traffic flows in a given network are widely studied in the literature, see, e.g., Ref. [21] for a review. Congestion effects in public transportation networks have received an increased interest in recent years [22], where it affects both travel times [23] and the user comfort [24].

A variety of models has been developed to analyze and optimize the structure of transportation networks, including traffic networks [25–27] as well as other types of technological or biological networks [1–6]. Fundamental results have been obtained for the elementary case of uncongested networks, but empirical studies reveal a growing importance of congestion [28]. Empirical results on how congestion shapes the shape of cities were presented in [11]. Abstract network models that explore the impact of congestion on the optimal structure were introduced in [29,30].

In this paper, we study the impact of congestion on the optimal shape of transportation networks [26]. We focus on three fundamental geometries that are frequently observed in subway or tram networks. Exemplary real world networks and the corresponding regularized geometries are shown in Fig. 1: Starting with a regular star shape (e.g., Saint Petersburg metro), we extend the network by allowing for two additional geometrical features that occur frequently in subway or tram networks: a cycle around the city center (e.g., Moscow, Paris) and the branching of tracks in the outskirts (e.g., Hannover). For each geometry, we then optimize the network structure to minimize the travel time from the city to its center for three radially symmetric models of the population densities as sketched in Fig. 1(d). Finally, we map out the optimal geometry as a function of the available resources and the importance of congestion and analyze the transitions between different optimal shapes. We note that further modes of transportation exist in many cities which can provide additional structural features. For instance, bus lines may provide cycle lines instead of a metro.

Our work builds on a previous article by Aldous and Barthelemy, which addressed the corresponding problem in the absence of congestion [26]. We introduce a versatile numerical method to determine travel time in the presence of congestion and thus choose the best network. Furthermore, we extend the investigation to polycentric cities and study two central properties of supply networks: the occurrence of loops or circle lines and the branching of tracks.

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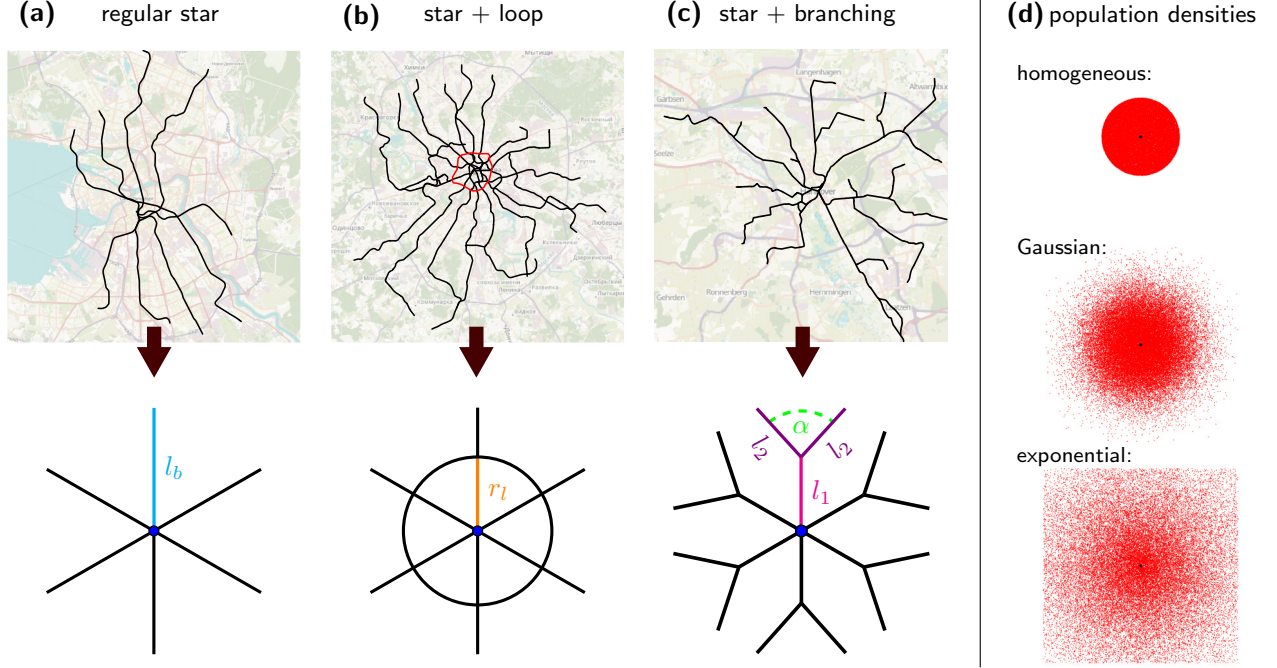


FIG. 1. Structural patterns in urban transport networks. The geometries of public transport networks feature a large variety of structural elements leading to very individual shapes. However, some elementary patterns can frequently be observed. In this paper, we discuss the optimal shape of three of these fundamental patterns: (a) The shape of the Saint Petersburg metro is close to a star network where several straight lines cross each other only in the city center. This topology can be idealized to a *regular star* with n isotropical branches of length l_b . (b) The Moscow metro network features in addition a loop track around the city center (red). In this paper, we thus secondly investigate a regular star extended by a concentric loop with radius r_l . (c) The Hannover tram network is a typical example for branching in the outskirts of the city. To study this type of geometries, we thirdly consider a star network where each branch splits at a distance l_1 from the city center into two subbranches of length l_2 which span an angle α . (d) We study the optimal geometries for three different radial symmetric population density distributions: a homogeneous disk, a Gaussian density and an exponential density. Each red dot represents an inhabitant, which are randomly distributed according to the respective density function. The black dot marks the city center. Map data based on OpenStreetMap [31].

II. METHODS

The central objective of this article is the structure of optimal transportation networks: Given a limited budget, what is the optimal shape of the network such that the overall travel time is minimized? In the following, we will formalize this optimization problem and introduce several key methods to solve it.

A. Objective function

Consider a city that is modeled as a two-dimensional area, such that each point in the city can be described by a vector in the plane $\mathbf{x} = (x_1, x_2)^T \in \mathbb{R}^2$. We assume that the population density in the city is described by the function $\rho(\mathbf{x})$ and that all inhabitants want to travel from their home place to other places, which are described by a distribution of destinations $\rho_d(\mathbf{y}|\mathbf{x})$. We may then calculate the average travel time τ for all journeys in the whole city by integrating over the destination and population densities

$$\tau = \int d\mathbf{x} d\mathbf{y} \tau(\mathbf{x}, \mathbf{y}) \rho(\mathbf{x}) \rho_d(\mathbf{y}|\mathbf{x}), \quad (1)$$

where $\tau(\mathbf{x}, \mathbf{y})$ is the travel time between two points $\mathbf{x}$ and $\mathbf{y}$. This expression for the average travel time τ is the central objective to be minimized. The solution of this optimization problem depends on the properties of the city [via the

functions $\rho(\mathbf{x})$ and $\rho_d(\mathbf{y}|\mathbf{x})$] as well as the methods of transportation that determine $\tau(\mathbf{x}, \mathbf{y})$. In particular, we assume that the resources are limited, which is quantified by an upper bound to the total network length L . Hence, we will evaluate the optimal network geometry as a function of the total network length L throughout this article.

Cities and their spatial structures are complex systems that are subjects to ongoing research [32]. In classical urban economics, a fundamental approach to study cities is the monocentric model [33,34], which assumes that most of the economic activities are concentrated inside a small area in the city center, the *central business district* (CBD). We therefore focus the first part of the analysis on this fundamental city model. In the second part, we generalise the analysis for nonmonocentric cities as many cities reveal a decentralized and more complex spatial organization [35–38].

Using the model of a monocentric city, we assume that most travelers want to go to the CBD and travelers seeking to reach other locations can be neglected. For simplicity, we assume the CBD to be pointlike and located in the origin $\mathbf{0}$ of the coordinate system. The distribution of densities then reads $\rho_d(\mathbf{y}|\mathbf{x}) = \delta(\mathbf{y})$. Imposing ρ_d into Eq. (1), the average travel time for a monocentric city becomes

$$\tau = \int d\mathbf{x} \tau(\mathbf{x}, \mathbf{0}) \rho(\mathbf{x}). \quad (2)$$

Thus, it remains to minimize the average timelike distance to center $\tau(\mathbf{x}, \mathbf{0})$ for each traveler.

B. The average travel time in multimodal traffic networks

The average travel time τ is essentially determined by the available modes of transport and their velocities. In this article, we assume that there are two modes of transports: People can either walk or use a transportation network such as a subway network. Typically, people will have to use both modes of transport, first walking to the network, then traveling along the network and then eventually walking again. Hence, the traveling time $\tau(\mathbf{x}, \mathbf{y})$ is the sum of the traveling time along both modes which we will now discuss in detail.

First, people can walk in the plane between any two points with a constant velocity v_w , which we set to 1 in appropriate units. Assuming that people can walk directly and that no congestion applies here, the walking time between two points $\mathbf{x}$ and $\mathbf{y}$ is simply given by $\|\mathbf{x} - \mathbf{y}\|/v_w$, where $\|\cdot\|$ denotes the euclidean distance.

Second, people may choose a transportation network, for example a subway network. This mode is typically faster than walking but also longer. We assume that travelers seek to minimize the total travel time τ , which is obtained by summing up the travel time along the path on the network.

In this article, we are especially interested in the impact of congestion within the transportation network on the average travel time τ and the optimal network structure. Congestion is taken into account by assuming that the travel time τ_l along a link l increases monotonically with the respective flow F_l . In particular, we assume a linear relation

$$\tau_l(F_l) = (a + bF_l)d_l, \quad (3)$$

where d_l is the length of link l and b a congestion parameter that is discussed in detail below. The parameter $a = 1/v_0$ is the inverse of the free-flow velocity v_0 , i.e., the velocity in the limit $F_l \rightarrow 0$. For a subway network, a typical value for a is $a \approx 1/8$, assuming $v_w \approx 5 \text{ km/h}$ and $v_0 \approx 40 \text{ km/h}$. Throughout this article, we thus use $a = 1/8$.

The congestion parameter b describes how strongly the flow F_l increases the physical or equivalent travel time along a link l . It thus measures how susceptible the network is to congestion induced delays. The impact of congestion vastly differs between cities and times of the day (for example, rush hour versus night). We thus keep b as a free parameter and show results as a function of $b \in [0, 4]$ in units of v_w over the flow density normalized by the city population. To get an impression of the meaning of this parameter, consider Eq. (3): The ratio a/b gives the amount of people that need to travel along a single line to double the travel time. For $a = 1/8$ and $b = 4$, we find that the travel time along a line is doubled when approximately 3 % of the city population take this line.

Before we proceed, we briefly comment on the fundamentals of the congestion model used in this study. Congestion effects are intensively studied for road traffic, where different functional relations $\tau_l(F_l)$ have been used [39,40]. We can interpret Eq. (3) as a generic Taylor expansion of these functions up to linear order. In case of heavy congestion, the linear function will cease to be a good approximation and must be replaced by a more general function $\tau_l(F_l)$. Furthermore,

heavy congestion in road traffic typically leads to dynamical phenomena such that the assumption of a quasisteady flow is no longer justified. Hence, our results rather apply to the case of medium congestion.

Congestion is also important in public transportation networks [22], where it can affect routing decisions in two ways. First, congestion can increase the physical travel times due to denied boarding or irregular vehicle arrivals [23]. Second, overcrowding reduces the comfort and thus the effective utility of travelers, which may choose alternative routes or modes of transportation [23,24]. A quantification of these effects is more involved as in the case of physical traveling times; yet several studies confirm the impact of congestion on route choices in public transportation [41–43]. Notably, the effect of discomfort has been quantified in terms of an equivalent increase of travel times in empiric studies [44], using a linear functional relationship as in Eq. (3).

Once we fixed the traffic flow model, it remains to determine for each traveler the stations where he enters and leaves the network. In the main part of the manuscript we assume a “lazy traveler” model, where each traveler uses the station that is next to his starting point and destination, respectively, to minimize the length of his walking path. Other routing strategies are discussed and evaluated in Appendix A. We find that the results are very similar such that we focus on one strategy in the main text.

C. Numerical optimization

To solve the integral in Eq. (2) for complex city and network shapes, we developed a versatile method that evaluates the average travel time τ using a discretization of both the network, the starting points and the destinations. In particular, the solver proceeds as follows (cf. Fig. 2):

- (1) Draw N starting points at random according to the population density $\rho(\mathbf{x})$.
- (2) Place destinations according to the current model of the city structure by drawing at random from the distribution $\rho_d(\mathbf{y}|\mathbf{x})$.
- (3) Add stations for entry and exit to a given network. Place one station in the center [blue circle in Fig. 1(b)]. Proceed outward on the radial branches and place stations in intervals of length Δl . Add one additional station at the end of the radial branches. If the network contains a loop or branches, a station is added at each crossing point. Further stations are added along a loop such that their mutual distances are equal and as close to Δl as possible.
- (4) Routing: Compute the optimal path to the destination for each starting point according to the corresponding routing strategies. Travelers can only access or leave the network at a station. Thus, we seek the station for each traveler where they enter and leave the network.
- (5) Compute the flow F_l and the resulting travel time $\tau_l(F_l)$ for every segment l of the network, that is a connection between neighboring stations. The flow F_l is directly proportional to the number of travelers using this segment of the network.
- (6) Sum up the traveling times for each starting point to obtain $\tau = \tau_w + \tau_s$. While the average walking time τ_w equals the Euclidean distance from each starting point to its access

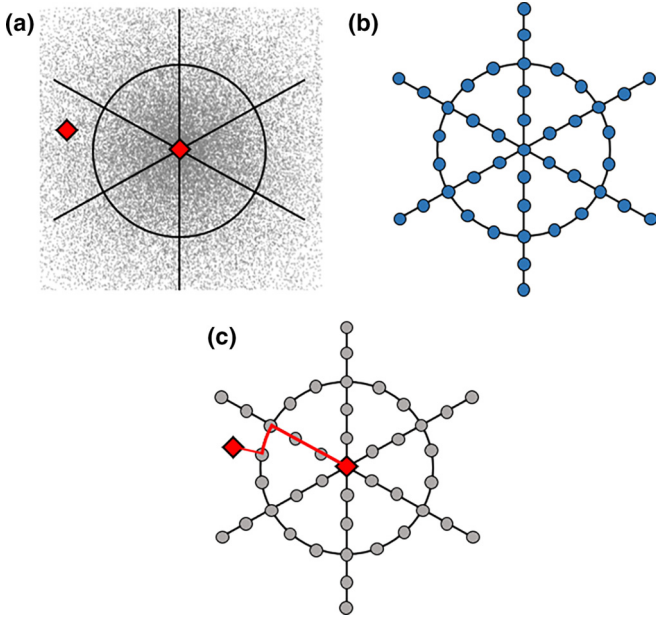


FIG. 2. Main steps of the simulation scheme. (a) The origin and destination of each traveler (red diamonds) is drawn at random from the distributions $\rho(\mathbf{x})$ and $\rho_d(\mathbf{y}|\mathbf{x})$. (b) The network (black lines) is initialized using one of the three geometries shown in Fig. 1 and stations (blue disks) are placed along the network. (c) The traveler chooses a path (red line) from origin to destination according to a specified routing strategy. Finally the travel time is computed taking into account the effect of congestion, and summed up over all travelers.

station of the network plus the distance from the exit station to the destination in appropriate units. The average travel time τ_s inside the network is the sum of the travel time τ_l for each segment l of the network multiplied with the local flow F_l .

Further details of the numerical solver are described in Appendix C. Throughout the paper, we use $\Delta l = 0.05 r_0$, which corresponds to a station distance $\Delta l \approx 500$ m for a city of size $r_0 \approx 10$ km.

We note that all users individually compute an optimal path. Traffic research generally distinguishes between user equilibrium traffic and system optimal traffic, which do not necessarily coincide [45]. Routing decisions in equilibrium are generally affected by the decisions of all other travelers, which is not included in the current simulation. It has been checked for selected cases that this simplification does not have a significant effect for the given elementary network structures. The computation is substantially complicated when stochastic fluctuations or traffic information is taken into account [45,46]. Furthermore, we note that in real public transportation networks stations are typically not placed at a constant distance but locations are adapted to the demand. The optimal placement of stations is beyond the scope of this paper.

D. Population densities

As the optimal network shape depends on the distribution of the population in the city, we performed the optimization

for three different radial symmetric population density functions $\rho(r)$ as shown in Fig. 1(d):

(1) compact homogeneous disk with a constant density up to a distance r_0 from the city center with $\rho_{\text{hom}}(r) = \rho_0 \Theta(r_0 - r)$, where Θ denotes the Heaviside step function;

(2) Gaussian density with $\rho_{\text{gauss}}(r) = \rho_0 \exp(-r^2/r_0^2)$, where a small part of the population is located further away from the city center; and

(3) exponential density with $\rho_{\text{exp}}(r) = \rho_0 \exp(-r/r_0)$, which yields a widely spread population.

The prefactor ρ_0 is chosen such that the overall population is normalized to $\int \rho(r) dr = 1$. The factor r_0 classifies the typical scale of the city. Throughout this manuscript, we set $r_0 = 1$ and express all lengths in units of this parameter. For real cities, the value of r_0 typically lays in the order of a few kilometres. We note that the exponential distribution is commonly regarded as the best model for the population density of a city, based on both empiric investigations and theoretic economic models [47].

E. Travel time without a network

To quantify the benefits of a transportation network, we compare the average travel time to the case without any transportation network.

In a monocentric city without a transportation network, we have $\tau(\mathbf{x}, 0) = \|\mathbf{x}\|/v_w$ and the integral in Eq. (2) can be evaluated in closed form for the three different models of the population density

$$\tau_0 = 2\pi \int_0^\infty dr r^2 \rho(r) = \begin{cases} \frac{2}{3}r_0 & \text{homogeneous disk,} \\ 2r_0 & \text{Gaussian,} \\ \frac{\pi}{2}r_0 & \text{exponential.} \end{cases} \quad (4)$$

The ratio $\hat{\tau} = \tau/\tau_0 \in [0, 1]$ is the reduction of the average travel time by the network and thus quantify its effectiveness. We therefore use $\hat{\tau}$ as a measure of network performance throughout this paper.

III. RESULTS

A. Optimal shape of a regular star network

We first analyze the optimal geometry of a regular star network without loops and branching. The Saint Petersburg metro is an example for such a network as visualized in Fig. 1(a). The geometry is optimized by choosing the number of branches n such that, for fixed total length L of the network and congestion parameter b , the averaged travel time τ assumes its minimum. The results are plotted in Fig. 3 over the network length L .

As expected, both the optimal number of branches n^* [Figs. 3(a)–3(c)] and the corresponding branch length $l_b^* = L/n^*$ [Figs. 3(d)–3(f)] increase with the amount of available resources L . The optimal length l_b^* increases rapidly at first and then saturates, where the saturation level differs strongly for three models of the population density $\rho(\mathbf{x})$. In the homogeneous disk model, all travelers start at a distance below r_0 such that a track outside this radius will not be used. Hence, the optimal length l_b^* converges to r_0 from below. In the Gaussian model, the population density drops rapidly for

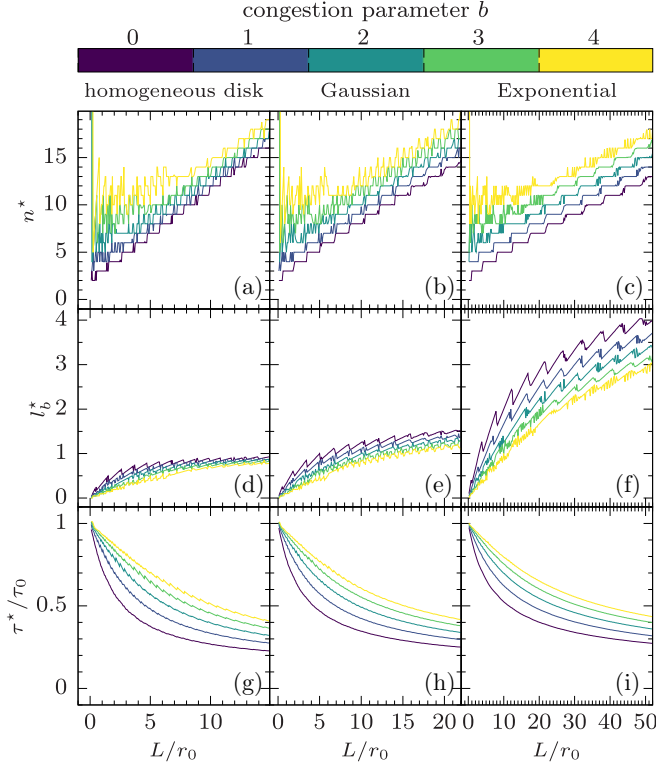


FIG. 3. Impact of congestion on optimal star geometries. We plot the optimal parameters for a regular star network [cf. Fig. 1(a)] over the network length L for different values of the congestion parameter b (color code): (a–c) The optimal number of branches n^* , (d–f) the corresponding branch length $l_b^* = L/n^*$, and (g–i) the optimal averaged travel time τ^* . We use the “lazy traveler” model for routing and compare three different models of the population density [cf. Fig. 1(d)]. We find that the optimal branch length l_b^* saturates depending on the population density model. Congestion favors more and shorter branches over fewer and longer ones.

$r > r_0$ such that l_b^* saturates for values slightly above 1. In the exponential model, the population density decreases much slower. Hence, l_b^* also saturates slower and at higher values. In contrast the optimal number of branches n^* does not saturate and grows almost proportionally with L . This implies that, with limited resources, one should first invest in the elongation of existing lines and only then invest into building new lines. In the following, we will mostly restrict our analysis to one population density for the sake of clarity.

When varying the congestion parameter b , we find that n^* increases with b and, consequently, l_b^* decreases. Since a growing congestion adds a penalty for strong flows on single branches, it is reasonable that in the presence of congestion more and shorter branches are preferred over fewer longer ones. Notably, congestion in real networks depends also on the frequency and capacity of trains, which is assumed to be constant in the current model.

B. Benefit-cost ratio for a regular star

In most applications, not only the optimal shape of the network needs to be determined but the benefit-cost ratio must also be evaluated to decide whether an investment is worth it.

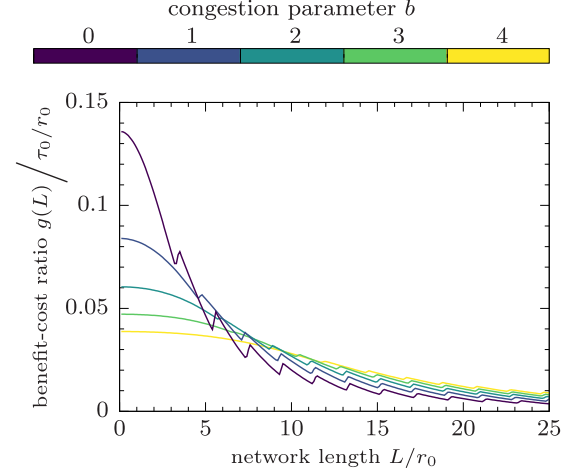


FIG. 4. Cost benefit ratio for network expansion. The cost benefit ratio $g(L) = -d\tau^*/dL$ for an optimal star generally network decreases with the network length L . In the presence of congestion, $g(L)$ is smaller for short network, but decreases slower with increasing L . Hence, extending the network becomes increasingly beneficial with higher levels of congestion, i.e., $g(L)$ increases with b , when the network is already large ($L \gg r_0$). We use the Gaussian population density model and the “lazy traveler” model.

We assume that the construction costs are proportional to the length L of the transportation network and define the benefit as the reduction of the optimum averaged travel time τ^* . The marginal

$$g(L) := -\frac{d\tau^*}{dL} \quad (5)$$

then gives the benefit-cost ratio for enlarging the network. The minimal averaged travel time τ^* is plotted in Figs. 3(g)–3(i) in units of the averaged travel time in absence of the network τ_0 . The corresponding benefit-cost ratio (5) is shown in Fig. 4 for the Gaussian population density.

For small networks, we find a high benefit-cost ratio while this value decreases approximately exponentially with growing networks, i.e., the longer the network, the less benefit we get from adding a unit length to the network. Considering congestion, we find that, with L fixed, τ^* grows with the congestion parameter b as a consequence of the reduction of speed within the network due to congestion. Therefore, the benefit-cost ratio $g(L)$ is lowered in the presence of congestion for short networks. In the case of long networks, however, we find that the benefit-cost ratio is increased by b . Nevertheless, the total benefit, i.e., the value of τ^* , is always lower for stronger congestion [cf. Figs. 3(g)–3(i)]. Thus, when building a network from scratch, the presence of congestion always lowers the benefit for a given investment. However, if an existing network should be enlarged, then congestion might even increase the benefit for a given investment.

C. Optimal loop radius

In the next step, we investigate a modification of the simple star network by adding a loop track around the city center as sketched in Fig. 1(b), which is commonly observed in real public transportation networks such as the Moscow metro,

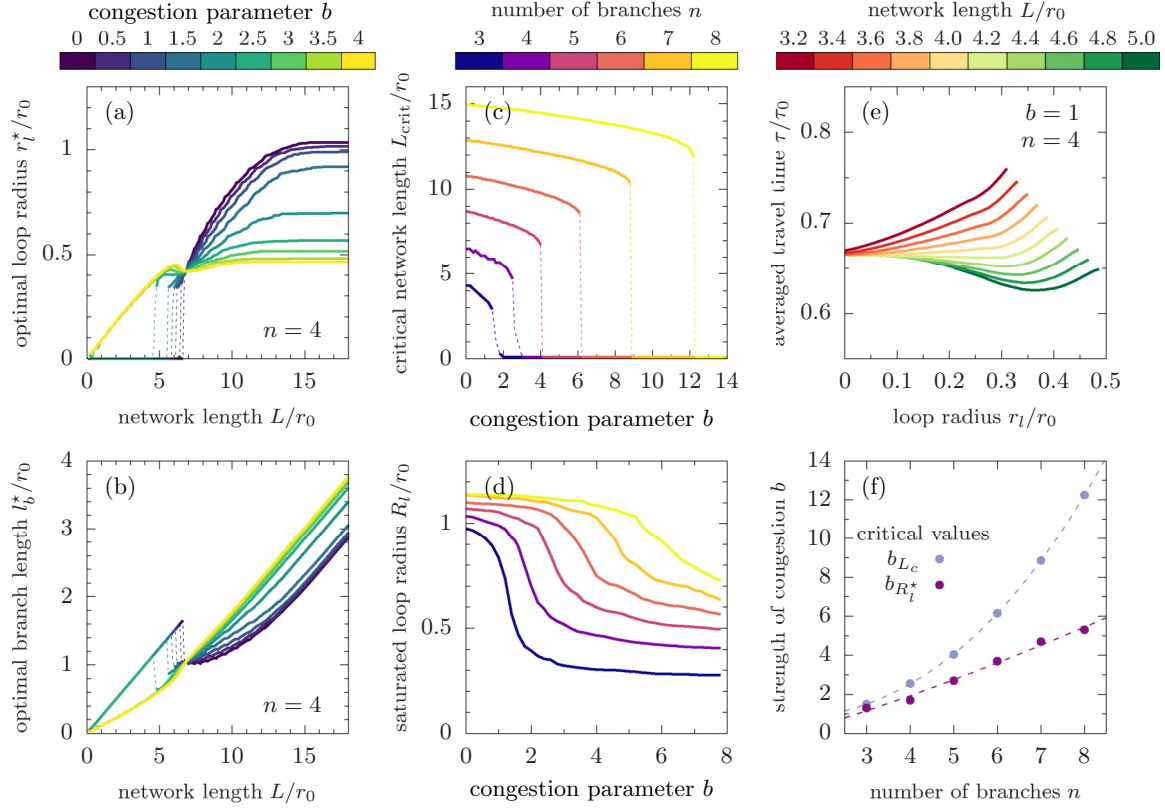


FIG. 5. Transition from nonloopy to loopy transportation networks is discontinuous. We plot the optimal parameters for a star with a concentric loop [cf. Fig. 1(b)] over the network length L for different values of the congestion parameter b using the Gaussian population density. the number of branches n is kept fixed in the optimization. (a) The optimal loop radius r_l^* jumps at a critical network length L_{crit} from zero (no loop) to a finite value. (b) Correspondingly, the optimal branch length l_b^* is also discontinuous at this point. (c) The critical parameter L_{crit} is also discontinuous when varying the congestion parameter b : For a critical value b_{L_c} of the congestion parameter L_{crit} jumps from a finite value to zero. (d) When considering the saturation values of r_l^* in the limit of large networks, denoted by R_l^* , we also find a sharp transition from a “low-congestion” to a “high-congestion” phase around a critical congestion parameter $b_{R_l^*}$. In this case, however, the transition is much smoother compared to the transitions in panels (a–c). (e) When plotting the averaged travel time τ over the loop radius r_l , we find an explanation for the discontinuity of r_l^* : Increasing L flattens the $\tau(r_l)$ curve until at the critical length L_{crit} , the minimum of the curve flushes from $r_l = 0$ to a finite value. (f) While $b_{R_l^*}$ scales linearly with the number of branches n , we find $b_{L_c} \propto n^{2.5}$.

the Paris metro and the Cologne tram network. We use the numerical approach introduced in the Sec. II to determine the averaged travel time τ . A regular star network with a loop is parametrized by two quantities: the number of branches n and the radius of the loop r_l . Given the total length of the network L , the branch length l_b is then determined by

$$L = nl_b + 2\pi r_l \Rightarrow l_b = \frac{L - 2\pi r_l}{n}. \quad (6)$$

To find the optimal values of the geometrical parameters n^* and r_l^* , we have scanned the parameter space and selected the values which minimize τ . As before, we analyze the results in dependence of the available resources L and the congestion parameter b .

The first important finding is that a pure star network is always superior to a loopy network for given resources L and a monocentric city. When optimizing over both n and r_l , we always find the optimal loop radius $r_l^* = 0$. This result is a direct consequence of the specific optimization problem considered in this paper: All travelers want to go to the city center, such that loopy lines oriented orthogonal to this

direction are not present in an optimal network. Many real public transportation networks do however feature loops to facilitate travel between other positions than the city center, cf. Sec. III E.

Nevertheless, when considering n to be fixed we find for certain parameters a finite value for the optimal loop radius. Thus, if the number of branches n is fixed, then there are parameter settings where including a loop into the network becomes beneficial. Such a situation can occur in practical applications where the geographical situation or the structure of the city might bias the choice of n but also where a star shaped network is already present and space for further branches is not available. Then the question arises if the budget should be fully invested to extend the existing branches or if a loop should be established.

We now further investigate this scenario and fix $n = 4$ in the following. Furthermore, we focus on the Gaussian population density and the “lazy traveler” model, as all other models yield qualitatively similar results. The optimal loop radius r_l^* as well as the corresponding branch length l_b^* in this case are plotted in Figs. 5(a) and 5(b).

Most importantly, we find a discontinuous transition for the optimal network shape. For short networks $L < L_{\text{crit}}$, the optimal structure is again a pure star with $r_l^* = 0$. As L increases above a critical value L_{crit} , the loopy network becomes superior and the optimal value r_l^* becomes nonzero. Remarkably, the transition is discontinuous in the sense that the optimal parameter r_l^* jumps at L_{crit} —i.e., the loop comes into being with a nonzero radius. Correspondingly, the optimal branch length l_b^* jumps around L_{crit} to a lower value as parts of the resources are now needed for the loop. For $L > L_{\text{crit}}$, the optimal radius r_l^* increases with L to some extent and then saturates at a value $R_l := \lim_{L \rightarrow \infty} r_l^*$. We note that such a discontinuous transition was already observed by Aldous and Barthelemy [26] and rigorously established for a different type of optimal networks by Kaiser *et al.* [6].

The discontinuity can be explained by plotting the averaged travel time $\tau(r_l)$ as a function of the loop radius r_l . For $n = 4$ and $b = 1$ fixed, Fig. 5(e) visualizes these curves for different network lengths L around the critical network length, which is in this case $L_{\text{crit}} \approx 4r_0$. For $L < L_{\text{crit}}$, the curves $\tau(r_l)$ are strictly monotonically increasing such that the minimum is always located at $r_l = 0$. At $L = L_{\text{crit}}$, the curve becomes flat around $r_l = 0$. For $L > L_{\text{crit}}$, the curves $\tau(r_l)$ have a negative slope around $r_l = 0$ and a new minimum emerges for positive values of r_l .

The saturation loop radius R_l and the critical network length L_{crit} are further investigated in Figs. 5(c) and 5(d). Both quantities depend on the number of branches n and the congestion parameter b . In both cases, we can distinguish a low- and a high-congestion phase with relatively stable values and very sharp transitions from one phase to the other. In the low-congestion phase, the saturated loop radius satisfies $R_l \approx r_0$. That is, the loop is established in the outskirts of the city if the available resources permit. We conclude that the prime function of the loop is to collect travelers from locations in the outskirts far away from the radial branches. In the high-congestion regime, the loop is established much closer to the city center (R_l is much smaller than r_0), pointing to a very different function of the loop.

We further investigate the transition points between the low- and the high-congestion phase. We define the critical congestion parameters b_{L_c} and $b_{R_l^*}$ as the points where the negative slopes of $L_{\text{crit}}(b)$ and $R_l^*(b)$, respectively, assume their maximum. Remarkably, the critical values do not agree and show a different scaling behavior with the number of branches n . We find a linear scaling for $b_{R_l^*} \propto n$ and a nonlinear scaling $b_{L_c} \propto n^{2.5}$ with the number of branches n shown in Fig. 5(f). The linear scaling of $b_{R_l^*}$ is a consequence of the choice of units. While we define the population of the entire city as a unit of traveler, the total population within the catchment area of a single branch is just $1/n$ of the city population. Thus, the flow on a branch scales with $1/n$ and therefore the impact of congestion does, too. As a consequence, the critical value of the congestion parameters should scale with n . The reason for the nonlinear scaling of b_{L_c} is subject to further research.

D. Branching

As a second extension to the simple star network, we consider a splitting of the branches at a distance l_1 from the

center [cf. Fig. 1(c)]. Such a pattern allows the network to better reach the outskirts by saving costs through the sharing of tracks close to the city center, where neighboring branches are close to each other. The network shape in this case is characterized by three parameters: the number of branches n , the length of the inner branch l_1 , and the angle α between the split branches. The length of the outer branches is then given by

$$l_2 = \frac{L - nl_1}{2n}. \quad (7)$$

The optimal parameter values are again determined using the numerical method introduced in Sec. II and a scan of the parameter space.

When optimizing over n , we again find the optimal geometry to be always a regular star. As in the preceding section, we thus consider the scenario of a fixed number n . We conduct the discussion here for $n = 5$ and the homogeneous population density. Given a certain amount of resources L we now have the decision whether to enlarge or split the branches to better cover the outskirts of a city. Keeping n fixed, we can distinguish three optimal shapes:

(1) n star: for small networks with $L < L_1$, the optimal length of the outer branches l_2^* is zero, i.e., the optimal shape is a regular star with n branches,

(2) Branching: for intermediate networks with $L_1 < L < L_2$, we find both l_1^* and l_2^* to be nonzero, i.e., the optimal geometry contains branching,

(3) $2n$ star: for large networks $L > L_2$, the length of the inner branch l_1^* diminishes and the angle spanned by the branches becomes $\alpha = 360^\circ/2n$, i.e., the optimal network corresponds to a regular star with $2n$ branches.

The optimal geometry parameters l_1^* , l_2^* and α are plotted in Figs. 6(a)–6(c) over the network length L for different values of the congestion parameter b . The corresponding optimal shape for each combination of L and b is visualized in Fig. 6(d). In contrast to the loopy case (cf. Fig. 5), we observe smooth transitions from one shape to another in the branching case: When passing the critical network length L_1 , the outer branch length l_2^* starts growing linearly with L without any significant jumps. Similarly, l_1^* linearly diminishes when approaching L_2 . Thus, both phase transitions are continuous in this geometry.

Considering the phase diagram in Fig. 6(d), we find that both critical values L_1 and L_2 decrease with growing congestion parameter b until they both vanish, $L_1 = L_2 = 0$, for $b \approx 2.5$. Beyond these values of b , the regular star with $n = 10$ branches is always superior to both other shapes. This behavior is consistent with our previous results on regular star networks. For large values of b , it is more important to distribute travelers onto many lines to mitigate congestion than to supply the outskirts of the city. Hence, congestion favors more and shorter branches over fewer longer ones.

We further quantify the dependence of the critical network lengths L_1 and L_2 on the choice of n . Empirically, we find that the impact of b scales with $n^{-4/3}$ while for b fixed, both L_1 and L_2 scale linearly with n . We thus deduce the scaling laws

$$\begin{aligned} L_1(n, b) &\approx (n-2)\tilde{L}_1(b/n^{4/3}), \\ L_2(n, b) &\approx (2n-1)\tilde{L}_2(b/n^{4/3}), \end{aligned} \quad (8)$$

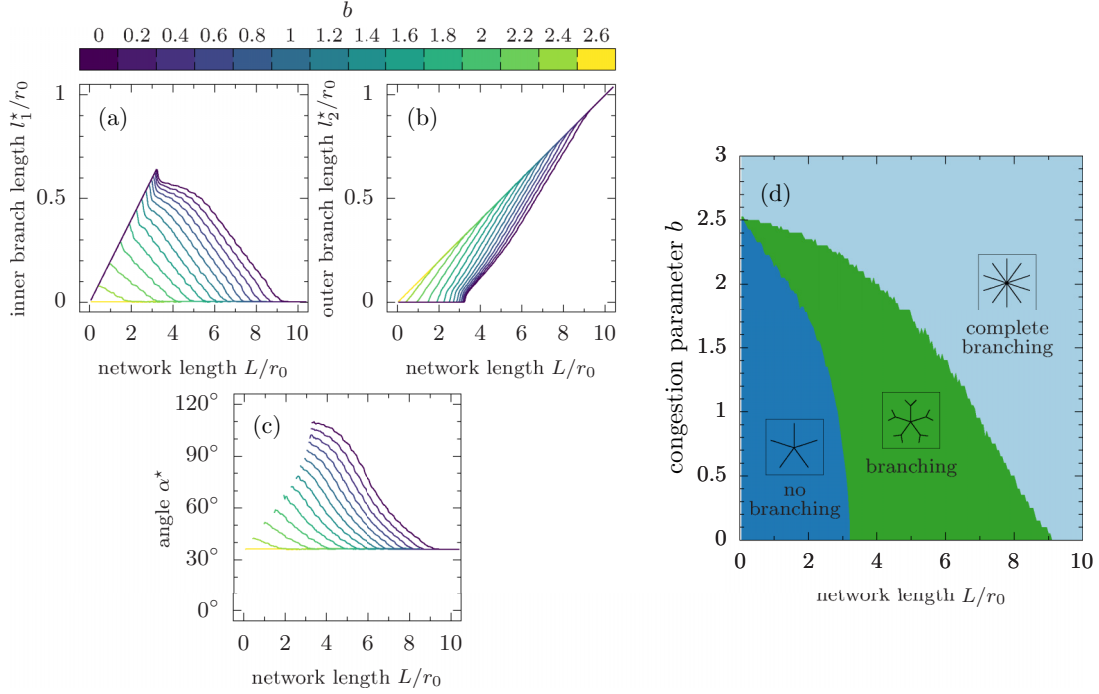


FIG. 6. Transitions in optimal branching topologies are continuous. We plot the optimal parameters for a star with branching [cf. Fig. 1(c)] over the network length L for different values of the congestion parameter b using the homogeneous population density and fixing the number of branches to $n = 5$. (a, b) Contrary to the loopy topology (cf. Fig. 5), we observe continuous transitions from one shape to another as both the optimal inner branch length l_1^* and the optimal outer branch length l_2^* are smooth functions of L . (c) For long networks, the optimal opening angle α^* spanned by the outer branches converges to $360^\circ/2n$ as l_1^* goes to zero, i.e., the branching topology passes into a regular star with $2n$ branches. (d) The phase diagram for the optimal shape at each point in the L - b plane reveals the impact of congestion: the stronger b , the smaller the critical network lengths at which the optimal geometry switches from one shape to another. We can spot a critical value of $b \approx 2.5$ above which the regular star with $n = 10$ branches is optimal for all L . When comparing this geometry with the loopy case, we find branching to be always superior to the loop.

with univariate functions $\tilde{L}_{1,2}$. Indeed, plotting $L_1/(n-2)$ and $L_2/(2n-1)$ as a function of $b/n^{4/3}$ the function largely collapse to $\tilde{L}_{1,2}$ as shown in Fig. 7. The reason for this empirically found scaling is subject to further research.

Considering the optimal angle α^* between the outer branches plotted in Fig. 6(c), we find that for small l_2 , the

angle starts at a large value and smoothly decreases to $\tilde{\alpha}^* = 360^\circ/2n$ for $l_1 \rightarrow 0$. Thus, the longer the outer branches, the closer they should lay together, but in any case the angle between them should be larger or equal to the angle of neighboring branches in a $2n$ star.

E. Optimizing transportation networks in polycentric cities

Many cities reveal complex spatial structures, that are shaped by a variety of parameters. In particular, growing cities typically experience a transition from a monocentric structure, which is strongly related to the limitation of traffic networks [37]. New subcenters or central business districts (CBDs) emerge at a certain distance, often where radial and peripheral highways cross each other (see, e.g., Ref. [36]).

Here, we generalise our analysis using a model for polycentric cities. Besides the CBD in the city center, N_c additional activity centers are isotropically distributed around the CBD at a distance R_c . In this model, we thus have $1 + N_c$ possible destinations for each traveler. We assume, that every traveler still wants to go to exactly one destination, which can be thought of, for instance, as the location of his working place. The precise mapping of each traveler's origin and destination depends on a variety of factors and is subject to current research [38]. Here, we assume the well established gravity

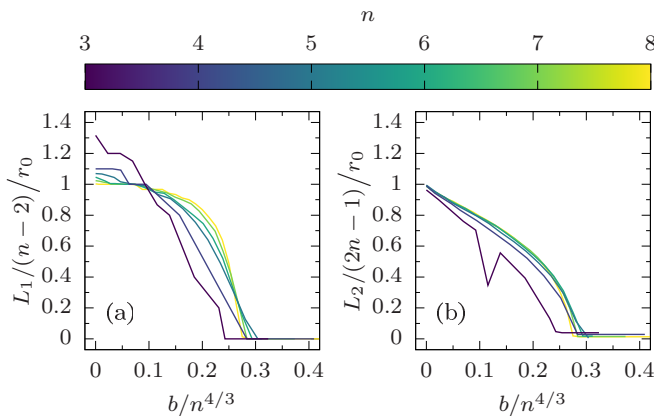


FIG. 7. Impact of congestion on the critical network length $L_{1,2}$. The numerical functions $L_1(n, b)$ and $L_2(n, b)$ largely collapse when they are plotted vs $b/n^{4/3}$ and rescaled by $(n-2)$ and $(2n-1)$, respectively. We thus conclude the scaling laws given in Eq. (8).

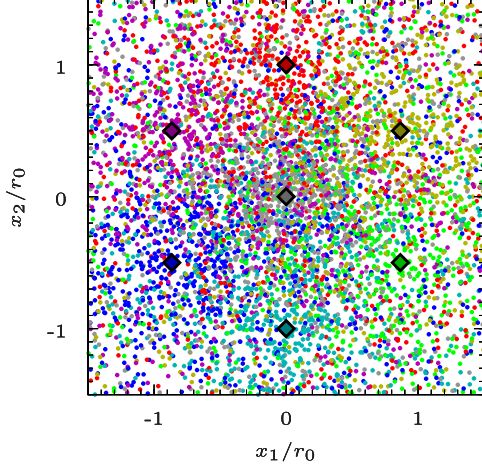


FIG. 8. Destination mapping using the gravity model. In a city with a population density that decays exponentially with the distance from the city center, each inhabitant is mapped to exactly one destination using the gravity model given in Eq. (9). Destinations are visualized as diamonds of different color. Each inhabitant is shown as a dot colored according to his destination.

model [48], where the probability $\rho_d(\mathbf{y}|\mathbf{x})$ of a traveler living at $\mathbf{x}$ getting mapped to a destination at $\mathbf{y}$ is proportional to the inverse of their Euclidean distance

$$\rho_d(\mathbf{y}|\mathbf{x}) \propto \frac{1}{\|\mathbf{x} - \mathbf{y}\|}. \quad (9)$$

In Fig. 8, the mapping is visualized for a city with an exponential population density and $N_c = 6$ subcenters at a distance $R_c = r_0$ from the center.

We now investigate the impact of additional subcenters on the optimal loop radius compared to the monocentric city discussed in Sec. III C. We keep the number of subcenters $N_c = 6$ fixed but vary their distance from the city center. The symmetry of this city suggests to implement a network with $n = N_c = 6$ branches that are placed such that each branch points into the direction of a subcenter. We thus focus the discussion on a star-shaped network with six branches plus a single loop around the city center. In particular, we consider the optimal loop radius r_l^* for different values of R_c Fig. (9a). We note that the monocentric case is equivalent to $R_c = 0$. To keep the analysis clear, we here discuss only the uncongested scenario $b = 0$.

We find that a pure star network is the best choice if the available resources are sparse, that is, if the total network length L is below a critical value L_{crit} . Remarkably, the critical value L_{crit} for the emergence of a loop is largely independent of the position of the subcenters R_c as long as they exist ($R_c > 0$).

If L is increased beyond L_{crit} , the optimal loop radius r_l^* rapidly increases to match the position of the subcenters R_c . This finding is intuitive as travelers can now use the loop track and exit the network directly at a respective subcenter. In the numerical results, we thus find a plateau where $r_l^* = R_c$. For even higher value of L , the loops leaves the subcenters and r_l^* increases beyond R_c before it finally saturates. In this regime, the loop track provides an improved accessibility to

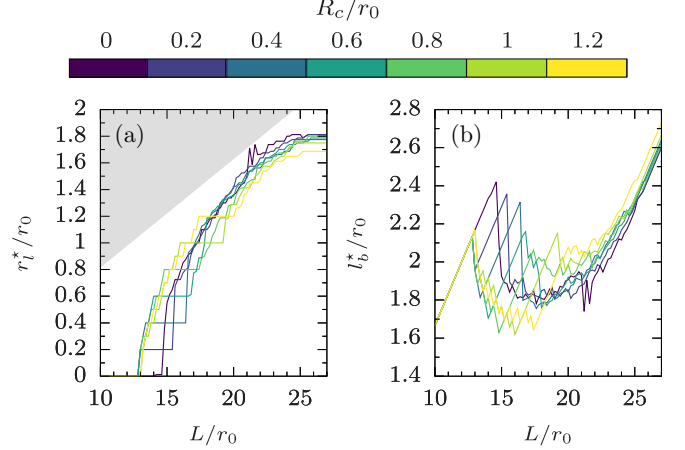


FIG. 9. Optimal loop radius in a polycentric city. Assuming a city with $N_c = 6$ subcenters at a distance R_c from the city center, we optimize the parameters of a network with $n = 6$ radial branches and one loop. (a) The optimal loop radius r_l^* is plotted over the total network length L for different values of R_c . The gray area marks the parameter range that would correspond to a disconnected network where the network branches do not reach the loop, i.e., where $r_l > l_b$. (b) The corresponding optimal branch length l_b^* is plotted over the network length L . We assume an exponential population density and the “lazy traveler” model.

the network for travelers from the outskirts of the city. The benefits of this effect outweighs the benefits of the direct access to the subcenters.

IV. DISCUSSION

In this article, we have analyzed the optimal shape of transportation networks for multimodal urban traffic in the presence of congestion. We have focused on three elementary network structures to quantify fundamental characteristics of optimal networks and the role of congestion. In the case where all travelers travel to the city center, a regular star network is always superior to a network with loops or branches in terms of overall travel time. However, this strict result only holds if the number of branches n can be freely adapted as the network is extended. In practice, multiple geographic constraints exist and the question arises whether one should rather invest into simple line extensions, branches or an additional loop track. Our results show that the answer to this question strongly depends on the available resources and the importance of congestion.

Our detailed analysis of loopy and branching networks has led to four main results:

(i) The optimal shape of a loopy network is subject to discontinuous transitions. That is, the optimal loop radius r_l^* varies discontinuously, jumping from zero to a finite value, as the amount of available resources L is increased. Remarkably, strong congestion can qualitatively alter this scenario and even suppress the discontinuity.

(ii) In contrast, the optimal shape of a branching network varies smoothly with the amount of available resources L . In fact, the optimal shape evolves from no branching to finite branching to complete branching continuously as L is

increased. Complete branching is always beneficial when the congestion is dominant.

(iii) Given that we focus on traveling to the city center, branching networks are always superior to loopy networks.

(iv) Finally, congestion generally favors more and shorter branches over fewer longer ones. That is, it becomes more important to distribute the travelers on many lines to mitigate congestion than to reach the outskirts.

In the future, these general findings should be tested in more realistic simulation studies. An empirical analysis of the 15 largest metro lines worldwide [13] has revealed a universal structural pattern including a core and quasi-one-dimensional lines extending to the periphery. The core is often—but not always—bounded by a cycle line and branching occurs in many but not all periphery lines.

We believe that the value of our approach lies not only in the general results, but also in the developed methodology. We have introduced a model for congested multimodal transportation systems, extending prior studies such as Ref. [26]. To account for the mathematical complexity of the optimization problem, we have developed a versatile numerical simulation framework, which can easily be adapted to a wide range of network geometries as well as different population densities, routing strategies and congestion models. A distinguished feature of our simulation model is that it includes the actual routing strategies of individual travelers. In the current study, we did not find a significant impact of the different strategies on the optimal network shape. However, when considering more complex scenarios, the routing behavior might gain importance. In the case of concurrent congested transport networks, where other modes of transport such as street traffic are present, congested networks have been shown to be prone to paradoxical behavior, where an extension of infrastructure actually increases congestion [49]. The proposed simulation model can be readily extended to investigate such phenomena and to include other nonlinear congestion models.

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APPENDIX A: ROUTING STRATEGIES

The travel time τ from a starting to a terminal point is determined by the chosen path. In general, travelers seek to minimize τ , but different constraints apply leading to slightly different routing strategies listed below. In all cases we assume that the traveler has no actual information about the load of the network. Hence, routing decisions are based on the travel times for $F_l = 0$.

(1) Fast traveler model: The traveler aims to minimize his individual travel time. He is free to move in the plane and chooses the entry/exit stations such that the sum of the travel times for walking and network travel assumes a minimum.

(2) Lazy traveler model: The lazy traveler aims to minimize the walking time. Hence, he always uses the entry/exit

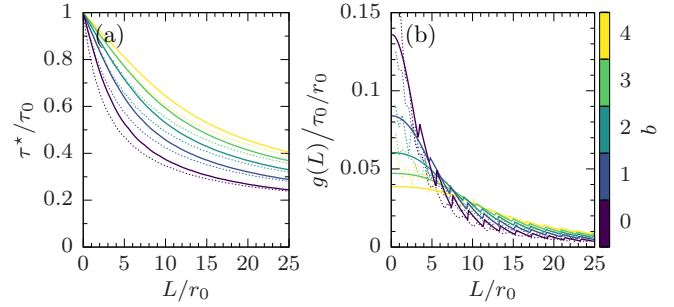


FIG. 10. Comparison of different routing strategies. We plot (a) the optimal travel time and (b) the cost-benefit ratio for different routing strategies: Results for the “lazy traveler” and the “fast traveler” are visually indistinguishable (dashed lines). Optimal travel times in the “polar grid model” are slightly higher. Results are shown for the Gaussian density.

stations that are nearest to his starting or terminal point, respectively.

(3) Polar grid model: We finally consider a model where travelers can only use a polar street grid. In this case, travelers will first walk inward on a radial path until they reach the radial distance of the closest access point to the network. Then, they follow the spherical path to this point to enter the network. Using this assumption, we give an analytical expression for the average travel time in a regular star shaped network in Appendix B. This model allows for a closed analytic expression for the average travel time for certain geometries; see Appendix B.

We find that the results for the “lazy traveler” and the “fast traveler” are virtually indistinguishable. The “polar grid model” includes stricter constraints such that the average optimal averaged travel time τ^* is slightly larger and decreases slower with the network length L . [Fig. 10(a)]. Similarly, the cost-benefit ratio $g(L)$ is smaller for $L \rightarrow 0$, and decreases slower with L as for the other routing strategies. As the polar grid has been introduced to enable analytic computations, we focus on the lazy traveler model for all numerical simulations.

APPENDIX B: ANALYTICAL SOLUTION FOR TRAVEL TIME IN CONGESTED STAR NETWORKS

In this Appendix, we derive analytical expressions for the averaged travel time τ in a city with a subway network of length L in the shape of a regular star with n branches using the “polar grid” routing strategy.

So consider a star network with n branches of length $l_b = L/n$ as depicted in Fig. 1(a). The main step in the solution of the optimization problem is the computation of $\tau(\mathbf{x}, \mathbf{0})$ given a radially symmetric population density $\rho(r)$. We assume that the network is accessible everywhere, i.e., we do not discretise this network as in the numerical approach. Furthermore, we assume that each traveler takes the shortest possible way toward the network following a radial or spherical path.

In the following, we denote the starting point as $\mathbf{x} = (x_1, x_2)$ in cartesian coordinates or by the radius r and the azimuth θ in polar coordinates. Furthermore, we can exploit the symmetry of the problem and consider only a single branch at $\theta = 0$ and travelers starting in the interval $\theta \in$

$[-\theta_n/2, +\theta_n/2]$ with $\theta_n = 2\pi/n$. Then the travel time of a single traveler is written as

$$\tau(\mathbf{x}, \mathbf{0}) = \frac{d_w(\mathbf{x})}{v_w} + \int_0^{d_s(\mathbf{x})} \frac{dr}{v_0(r)}.$$

The first two quantities, d_w and v_w denote the distance and velocity, respectively, that is spent walking which are used to calculate the time needed to go from $\mathbf{x}$ to the closest point on the network, where the traveler enters the subway. The second term gives the time spent within the public transportation network to drive from the access point at the radial coordinate $d_s(\mathbf{x})$ to the center along the branch. Using $v_w = 1$ and $v_0(r) = (a + bF(r))^{-1}$, this becomes

$$\tau(\mathbf{x}, \mathbf{0}) = d_w(\mathbf{x}) + a d_s(\mathbf{x}) + b \int_0^{d_s(\mathbf{x})} dr F(r). \quad (\text{B1})$$

The flow $F(r)$ on a branch at radial position r is proportional to the population living in the considered sector at a radial distance above v . Hence, we obtain the local flow on the branch by integrating over the population density of the area in which all travelers contribute to the flow at radius d_s

$$F(r) = \int_{-\theta_n/2}^{\theta_n/2} d\theta' \int_r^\infty dr' r' \rho(r') = \theta_n \int_r^\infty dr' r' \rho(r'). \quad (\text{B2})$$

To proceed further, we have to separate the population into two parts starting at a radius r smaller or larger than the branch length l_b . A traveler starting at a point with $r \leq l_b$ will go spherically to the next branch of the transportation network such that $d_w = |\theta|r$ and $d_s = r$. Integrating over all starting points with $r \leq l_b$ yields the contribution

$$\begin{aligned} \tau_1 &= \int_0^{l_b} dr r \int_{-\theta_n/2}^{\theta_n/2} d\theta \tau(\mathbf{x}, \mathbf{0}) \rho(r) \\ &= \theta_n \int_0^{l_b} dr r \rho(r) \left[\left(\frac{\pi}{2n} + a \right) r \right. \\ &\quad \left. + \theta_n b \int_0^r dr' \int_{r'}^\infty dr'' r'' \rho(r'') \right] \end{aligned} \quad (\text{B3})$$

to the total traveling time. A traveler starting further outward at a radius $r > l_b$ will first go inward radially until the traveler is on the same radial position as the outer end of the transportation network, and then proceed spherically to the branch. Hence, $d_w = (r - l_b) + |\theta|l_b$ and $d_s = l_b$ and we obtain the second contribution to the total traveling time,

$$\begin{aligned} \tau_2 &= \int_{l_b}^\infty dr r \int_{-\theta_n/2}^{\theta_n/2} d\theta \tau(\mathbf{x}, \mathbf{0}) \rho(r) \\ &= \theta_n \int_{l_b}^\infty dr r \rho(r) \left[r + \left(\frac{\pi}{2n} - 1 + a \right) l_b \right. \\ &\quad \left. + \theta_n b \int_0^{l_b} dr' \int_{r'}^\infty dr'' r'' \rho(r'') \right]. \end{aligned} \quad (\text{B4})$$

The total traveling time is then obtained by summing both contributions $\tau = n(\tau_1 + \tau_2)$. Solving the integrals for all

three population densities finally yields

$$\begin{aligned} \hat{\tau}_{\text{hom}}(\hat{L}, n) &= \begin{cases} 1 - \frac{3}{2}(1-a)\frac{\hat{L}}{n} + \frac{3}{2}\left(\frac{\pi}{2} + b\right)\frac{\hat{L}}{n^2} + \frac{1-a}{2}\frac{\hat{L}^3}{n^3} \\ \quad - \left(\frac{\pi}{4} + b\right)\frac{\hat{L}^3}{n^4} + \frac{3b}{10}\frac{\hat{L}^5}{n^6} \\ \quad a + \left(\frac{\pi}{2} + \frac{4b}{5}\right)\frac{1}{n} \end{cases}, \quad \hat{L} \leq n \\ \hat{\tau}_{\text{Gauss}}(\hat{L}, n) &= 1 + \left(\frac{\pi}{2n} + a - 1\right) \text{erf}\left(\frac{\hat{L}}{n}\right) \\ &\quad + \frac{b}{\sqrt{2}n} \text{erf}\left(\frac{\sqrt{2}\hat{L}}{n}\right), \\ \hat{\tau}_{\text{exp}}(\hat{L}, n) &= \left(\frac{\pi}{2n} + a + \frac{5b}{8n}\right) \\ &\quad - \left(\frac{\pi}{2n} + a - 1\right) \left(1 + \frac{\hat{L}}{2n}\right) e^{-\hat{L}/n} \\ &\quad - \frac{b}{n} \left(\frac{\hat{L}^2}{4n^2} + \frac{3\hat{L}}{4n} - \frac{5}{8}\right) e^{-2\hat{L}/n}, \end{aligned}$$

where $\hat{L} = L/r_0$ is the network length in units of the typical city size r_0 . The optimal value of the parameter n^* which minimizes τ and the corresponding $l_b^* = L/n^*$ is then computed numerically.

APPENDIX C: NUMERICAL SOLVER FOR CONGESTED FLOW NETWORKS

In this Appendix, we provide additional details on the numerical solver which computes the averaged travel time τ in the city for a given parameterized network geometry. It determines the optimal parameters for the given network geometry by scanning the parameter space.

The algorithm can be split into two parts: First, the city needs to be initialized. Second, for each point in the parameter space, the network needs to be initialized and routing takes place. In the following sections we will discuss these steps. Note, that this algorithm requires fully connected networks.

1. Step 1: Initialization of the city

In our model, some structures of the city do not depend on the specific implementation of the transportation network, so that we only need to initialize them once in the beginning and reuse these structures throughout the scan in the second part.

Namely, these structures comprise the starting point of each traveler as well as his destination, which are initialized within the following steps:

(1) *Draw starting points.* In a first step, we need to generate a population density distributed according to an arbitrary population density $\rho(x_1, x_2)$. We mimic the exact population density by placing N travelers in the plane using equally distributed random numbers. To obtain an accurate distribution of the population, we divide the plane into a grid of sufficiently small and equally sized cells and assume the population density to be constant within a single cell. Then, each cell is associated to a bin in a lookup table, where bin width is

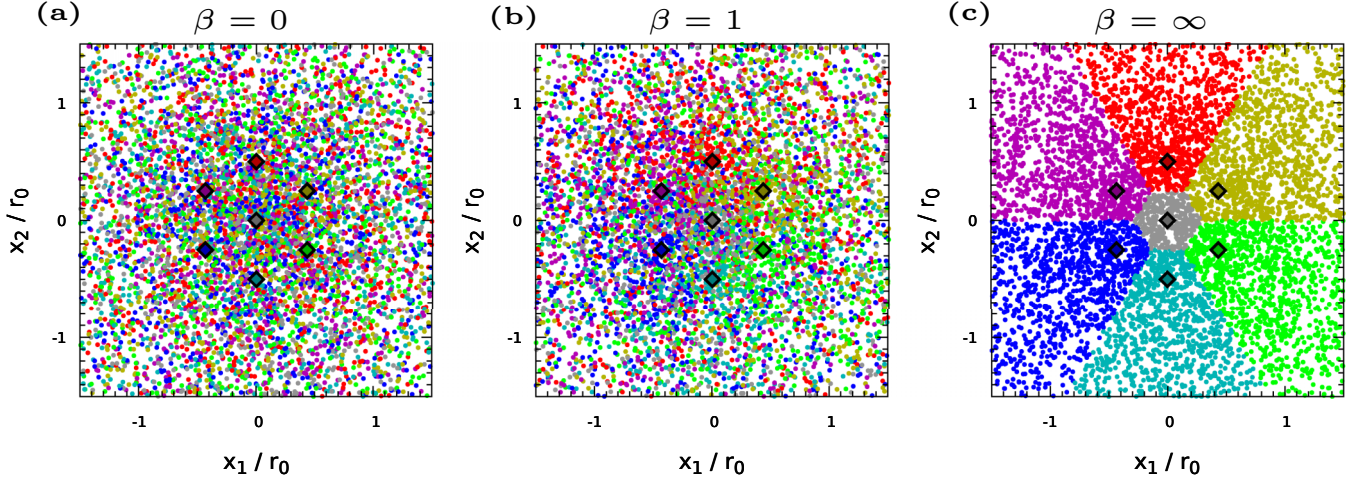


FIG. 11. Comparison of destination mapping models. Each diamond corresponds to a destination. Travelers are visualized as dots in the color of the destination they are mapped to. (a) For $\beta = 0$, travelers are randomly mapped to a destination, independent of their starting point. (b) Using a gravity model with $\beta = 1$, we observe an agglomeration of travelers close by a destination while still a significant amount of inhabitants need to travel to other parts of the city. (c) In the limit $\beta \rightarrow \infty$, we obtain extreme segregation where in each part of the city, all travelers are mapped to the closest destination.

proportional to population density ρ evaluated at the center of the cell. Once the lookup table is set up, we draw for each traveler three equally distributed random numbers to determine his starting point: The first random number determines via the lookup table the cell, within which the starting point is located. The second and third number define the position within this cell.

(2) *Draw destinations.* In a second step, the destinations are installed in the city. The number and distribution of them strongly depends on the underlying model for the city structure. We thus keep our solver flexible at this point to allow investigations for various models. We only assume that according to a model of choice, a set of D destinations is generated. Several travelers can be mapped to the same destination, so that D can be chosen independently from the number of travelers N .

In this manuscript, we use a toy model with one destination in the city center surrounded by N_c subcenters located isotropically at a distance R_c around the city center. This fundamental model allows both studying a monocentric city ($N_c = 0$) and polycentric cities ($N_c, R_c > 0$). Note, that the solver easily can be extended to locate the destinations according to an arbitrary destination density $\rho_d(y_1, y_2 | x_1, x_2)$ in the same way as it draws the starting points.

(3) *Map starting points and destinations.* Once all starting points and destinations are located, it remains to map each traveler having an individual starting point to a destination. We assume, that the probability, that a traveler with starting point $\vec{x}$ is mapped to a destination located at $\vec{y}$, decreases with the Euclidean distance $\|\vec{x} - \vec{y}\|$ as

$$\rho_d(\mathbf{x}|\mathbf{y}) \propto \frac{1}{\|\mathbf{x} - \mathbf{y}\|^\beta}. \quad (\text{C1})$$

This approach allows to study destinations mapping ranging from completely random mapping for $\beta = 0$ to a closest destination mapping for $\beta \rightarrow \infty$. The value of β might depend

again on the underlying models and parameters of the city, such as the ability of inhabitants to choose their starting points. In this manuscript, we consider $\beta = 1$ corresponding to the established gravity model [48].

After performing these three steps, we thus have a set of travelers, each having a starting point and a destination. In Fig. 11, this situation is visualized for a city with an exponential population density $\rho(\mathbf{x}) \propto e^{-\|\mathbf{x}\|/r_0}$ and a city with $N_c = 6$ subcenters at a distance $R_c = 0.5 r_0$ from the city center, visualized as diamonds. Travelers are mapped to a destination using different values for β and visualized as dots colored in the color of its destination.

2. Step 2: Initialization of the network

Once the travelers are mapped to a starting point and a destination, we need to provide a set of possible travel modes that the traveler can choose from to commute between both points. In this manuscript, we assume the travelers only have the choice between:

(1) *Walking.* Between any points in the plane, travelers can walk on any path with a constant velocity $v_w = 1$. Thus, the first possibility for a traveler to reach his destination is to walk along the straight line that connects his starting point and destination.

(2) *Walking and using the transportation network.* Besides walking, there is a transport network, that allows traveling along the network edges at a higher velocity, that might differ between different edges and depend on the local flow due to congestion. Thus, the second possibility is to walk at speed v_w to an access point of the network, traveling inside the network to an other access point, and finally walking again the remaining distance to the destination.

The transportation network is modeled by a set of nodes which corresponds to stations where travelers can enter the subway. The nodes are distributed in the plane according to the given network geometry with a distance Δl to

neighboring stations along the network branches. In this paper, we set $\Delta l = 0.05r_0$ which corresponds to a station distance of $\Delta l \approx 500$ m when considering a city with $r_0 \approx 10$ km. Note that in some cases, the distance between neighboring stations might differ from this value, e.g., to place the last station at the end of a branch. Each station s gets in addition to its position a list of inflow-destination pairs which count for each destination the number of travelers entering the network at this station.

The edges of the network connect the nodes according to the given network geometry. For each edge of network (r, s) connecting two stations r and s we have a flow F_{rs} such that the travel time along this segment reads

$$\tau_{rs} = (a + bF_{rs})d_{rs}, \quad (\text{C2})$$

where d_{rs} is the distance of r and s along the network.

3. Step 3: Routing

Once we have initialized both the endpoints of each travelers path and the network, we need in the next step to find for each traveler the best route to travel to his destination. There

are many different routing strategies that could be applied to define the best route for an individual traveler, depending on the travelers preferences, access to information and other parameters. Here, we consider three routing strategies as described in Appendix A. Most numerical results are shown for the “lazy traveler” model, for which routing consists of two steps:

(1) *Find closest stations.* For each starting point and for each destination, we determine the closest station in the network. Once we mapped each location to a closest station, we can compute for each station in the network the number of travelers that would enter the network here, as well as their target station, that is the closest station to their destination.

(2) *Choose path inside the network.* Once the entry and exit station are known for each traveler, the shortest path within the network can be computed using a standard shortest-path algorithm.

Once the routing procedure is done, it remains to compute the number of travelers for every segment (r, s) of the network to obtain $F_{r,s}$ and $\tau_{r,s}$. Finally, we compute the travel time for each traveler, which is then averaged over all travelers to obtain τ .

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