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Taming travel time fluctuations through adaptive stop pooling

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Supplementary material for this article is available online

Abstract

Ride sharing services combine trips of multiple users in the same vehicle and may provide more sustainable transport than private cars. As mobility demand varies during the day, the travel times experienced by passengers may substantially vary as well, making the service quality unreliable. We show through model simulations that such travel time fluctuations may be drastically reduced by stop pooling. Having users walk to meet at joint locations for pick-up or drop-off allows buses to travel more direct routes by avoiding frequent door-to-door detours, especially during high demand. We in particular propose *adaptive* stop pooling by adjusting the maximum walking distance to the temporally and spatially varying demand. The results highlight that adaptive stop pooling may substantially reduce travel time fluctuations while even improving the average travel time of ride sharing services, especially for high demand. Such quality improvements may in turn increase the acceptance and adoption of ride sharing services.

1. Introduction

In ride sharing systems, on-demand shuttles simultaneously transport multiple users in the same vehicle. Ride sharing services thus require fewer vehicles and may be ecologically and economically more sustainable than transport by private cars [1–6]. Yet users incur detours and travel longer than in private cars, especially if many users share the same vehicle, see figure 1(a) for an illustration. These detours may be reduced by *stop pooling* [2, 7, 8], where some users walk a short distance to a neighboring stop such that two or more users are served together at one pooled stop (figure 1(b)). With stop pooling the ride sharing vehicles, often (mini)buses, take routes that are more direct, avoiding detours and thereby improving both user experience and service efficiency. In particular, the average total travel time of users may decrease despite additional walking times [2].

However, ride sharing is challenged by demand fluctuations over the day [9, 10]—as demand data for ride hailing services in Manhattan (New York City, USA) exemplify [11, 12]. Higher demand often provokes higher travel times for users due to additional detours service vehicles need to make. Ride sharing providers might respond by adapting their system to maintain roughly constant travel times. One example response may be to adapt the fleet size [10, 13, 14], but an increase of the fleet size requires additional vehicles and drivers to be available, often not an economically viable option. Instead, we here propose to adaptively pool stops in order to reduce travel time fluctuations. The potential of stop pooling to reduce the travel time is known for steady state operation with constant demand [2]. This potential is higher at higher demand where it is easier to combine close-by stops [15]. However, the effects of stop pooling on the collective dynamics of ride sharing systems under varying demand has yet to be understood.

In this article, we demonstrate that stop pooling may reduce travel time fluctuations at a constant fleet size. Typically, the travel time increases with the demand. Stop pooling absorbs parts of the increase when users walk further at higher demand. For this purpose, we suggest two simple procedures to adapt the maximum walking distance, i.e. the maximum distance a user may be asked to walk, to the temporally and

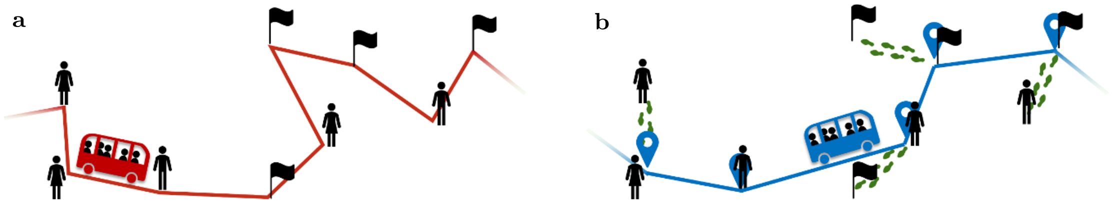

Figure 1. Ride sharing buses might reduce detours when users accept short walks. (a) Door-to-door ride sharing routes directly visiting every stop contain large detours when many users share one bus. (b) With stop pooling, buses might serve multiple users at shared stops. Some users walk a short distance to a nearby stop such that the bus route is more direct.

spatially varying demand. Both procedures significantly reduce the fluctuations of the travel time without any adaption of the fleet size.

2. Methods

To analyze the qualitative effects of stop pooling on the collective dynamics of ride sharing and in particular how stop pooling changes fluctuations in the travel time, we introduce an event-based model (details in supplementary note 1 and 2 citing [16–24] and in [15]) with three different events: (i) users request trips from an origin to a destination, (ii) ride sharing buses pickup users and (iii) deliver them. New users request trips while buses serve other users. Finding the bus routes is thus an online-optimization problem [5, 25]. A simple ride sharing algorithm assigns the users to buses (details in supplementary note 1.C). The algorithm minimizes the total distance driven by all buses while distributing users over all buses. The algorithm includes rebalancing [8, 26–28], i.e. sending back idling buses towards a central location to avoid that empty buses get stuck in regions of low demand (details in supplementary note 1.C.4).

With stop pooling, users might walk at most a maximum walking distance r per stop with user walk velocity v_u. When a user could walk from their desired stop to the stop of another user within time $\tilde{r} = r/v_\mathrm{u}$ and (if walking from origin to pickup) arrives at the stop of the other user before the bus, both stops are pooled. In this way, the algorithm finds locations of the pooled stops dynamically based on the current demand. If users request a very short trip with trip length $\ell \leqslant 2r$ they walk their complete trip (details in supplementary note 1.B, see [29]). All in all, the system saves at least one stop compared to standard ride sharing services if a user walks.

We include street network and request data from an example city into the model for interpretable results (details in supplementary note 2). We take origins, destinations and request time from a data set of taxi cabs in Manhattan (New York, USA) as in 2016 [11] (supplementary note 2.E). On a typical day, these requests are served by 7000–8000 taxis and even the minimum required taxi fleet would contain almost 6000 taxis [14]. We simulate a ride sharing service with a much smaller fleet size $B = 1500$. Buses drive along a directed street network of Manhattan [30, 31] that is fine-grained analogously to [32] (details in supplementary note 2.D). Buses drive with a mean-field velocity $v_\mathrm{b} = 12$ km h^{-1}—a typical average velocity for driving in Manhattan [33]. Decelerating, serving users and accelerating is represented by a constant penalty of 10 s per stop (common for public transport [34]), independent of the number of users entering or exiting the bus at that stop (details in supplementary note 1.C.3). Users walk on an undirected user network that contains the same nodes as the bus street network, but allows users to walk into both directions and to cross the street with a penalty of 10 m at additional nodes (see supplementary note 2.D). Users walk with user velocity $v_\mathrm{u} = 4$ km h^{-1}. The maximum walk distance r is thus equivalent to a walk time limit $\tilde{r} = r/v_\mathrm{u}$.

We conduct simulations with steady state dynamics by randomly sampling requests from all data and choosing request times from a Poisson distribution with constant request rate λ. We conduct simulations with the actually served taxi trips with varying request rates $\lambda(\tau)$ as resulting from the data of individual requests averaged across ten-minute intervals (see figure 2(a) on one example day between 6:00–24:00 (details in supplementary note 2.E). Besides, the spatial demand pattern deviates in the morning from the evening [12, 15]. We observe the travel time t that consists of wait time t_wait, drive time t_driv and walk time t_walk (details in supplementary note 3.F.1 citing [34,35]). For steady state simulations, we average all observables over all users. For fluctuating demand, we average all observables within intervals of one hour. Users contribute to that interval in which they pose their request. In all figures, the averages per time interval are represented by one data point in the center of the interval. We evaluate only times after one hour of simulation time, because simulations start with empty buses randomly distributed over all nodes. In the first hour of simulation time, buses accumulate a planned job list and distribute according to the requests. We calculate the request rate λ for each interval from the number of requests divided by the length of the time

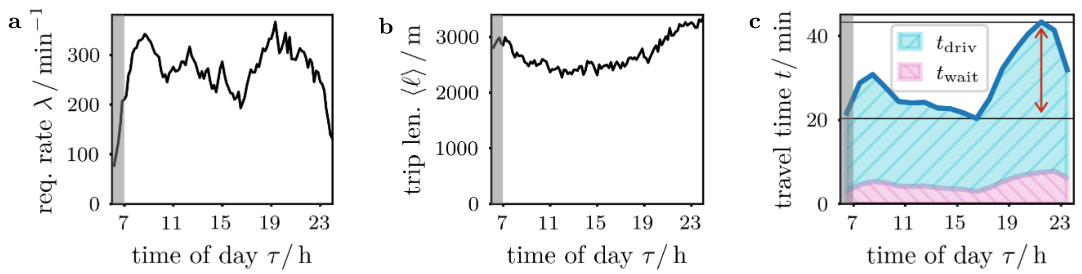

Figure 2. The travel time in standard ride sharing strongly varies with demand. (a), (b) Trip demand, i.e. the total trip length requested jointly by all users, varies strongly with the time of day τ. Panel (a) illustrates fluctuating request rate λ and (b) varying average trip lengths $\langle \ell \rangle$ for one day of requested trips in Manhattan, New York City (based on taxi requests, see Methods for details). (c) Consequently, the travel time t for users fluctuates as well, more than doubling from the minimum at 16:30 to the maximum at 21:30 (red arrow). This variability originates mainly from fluctuations in the average user drive time t_{driv} (blue shaded) that is much larger than the wait time t_{wait} (pink shaded). λ and $\langle \ell \rangle$ averaged across ten-minute intervals; travel times t averaged across one-hour intervals, trips requested in the interval.

interval. Except for the varying demand, input parameters (e.g. fleet size, velocities) are constant over the simulation.

3. Results

3.1. No stop pooling

First, let us consider the collective dynamics and fluctuations in standard ride sharing without stop pooling, $\tilde{r} = 0$. As the demand fluctuates over the day, the user travel time fluctuates as well (figure 2). For the example shown, the request rate λ varies with mean 275 min^{-1} and standard deviation 44 min^{-1} (16% of mean) between 7:00 and 24:00 (figure 2(a)). At the same time, the average trip length $\langle \ell \rangle$ of the users varies with mean 2675 m and standard deviation 289 m (11% of mean) (figure 2(b)). We consider demand as requested trip length characterized by request rate λ and average trip length ℓ. The demand is particularly small around 16:00 (neglecting the boundaries) with minimum request rate $\lambda = 193$ min^{-1} and more than 50% higher around 20:00 with maximum request rate $\lambda = 366$ min^{-1}.

The resulting travel time t with standard ride sharing fluctuates even more strongly, with mean 29.3 min and standard deviation 7.3 min (25% of mean). In the example, users who request a ride between 21:00 and 22:00 travel on average twice as long as users who requests a ride between 16:00 and 17:00 (table 1, figure 2(c), comparable distributions of individual travel times in both intervals, see supplementary note 3.G, figure S10). Such high fluctuations make the travel time unreliable for ride sharing users.

3.2. Static stop pooling

Static stop pooling, i.e. stop pooling with fixed walk time limits, already influences the collective dynamics of ride sharing. We thus compare results for different maximum walking distances $\tilde{r} > 0$ with those for standard ride sharing, $\tilde{r} = 0$ (no stop pooling). We find that with stop pooling, the travel time t may fluctuate less (figure 3), because (i) stop pooling may reduce the travel time t in general, compare also [2], and (ii) the reduction is typically higher the higher t at $\tilde{r} = 0$.

When users walk at most $\tilde{r} = 3.75$ min per stop (intermediate walk limit), the travel time t reduces compared to standard ride sharing at most times τ of the day (figure 3(a)) and also on average (table 1). This reduction might seem counterintuitive, because stop pooling requires additional time t_{walk} for walking (figure 3(b)). However, the reduction is explained by a trade-off of additional walk time and reduced drive time: With a fixed walk limit $\tilde{r}$, the walk time t_{walk} is roughly constant despite fluctuating demand (figure 3(c)). Indeed, users walk on average less than the maximum $2\tilde{r}$ ($\tilde{r}$ at origin and destination) and even less than $\tilde{r}$ (table 1). When some users walk to pooled stops, ride sharing buses drive to fewer stops and reduce some detours such that the bus routes become more strongly directional. Users profit from such more direct bus routes due to shorter average drive times t_{driv} (figure 3(b)). A sufficiently large reduction of t_{driv} overcompensates additional walk times (figure 3(c)). The reduction is higher at high demand, because many users share one bus. With many users, bus routes in standard ride sharing contain many small detours that stop pooling might save. There is a high potential to reduce t_{driv}. In the example, the travel time reduction is particularly high in the demand peak in the evening and rather small in the demand minimum around 16:00 (figure 3(c)). In consequence, the travel time t varies less with stop pooling (standard deviation 5.4 min, 21% of mean at $\tilde{r} = 3.75$ min) than with standard ride sharing, $\tilde{r} = 0$ (table 1).

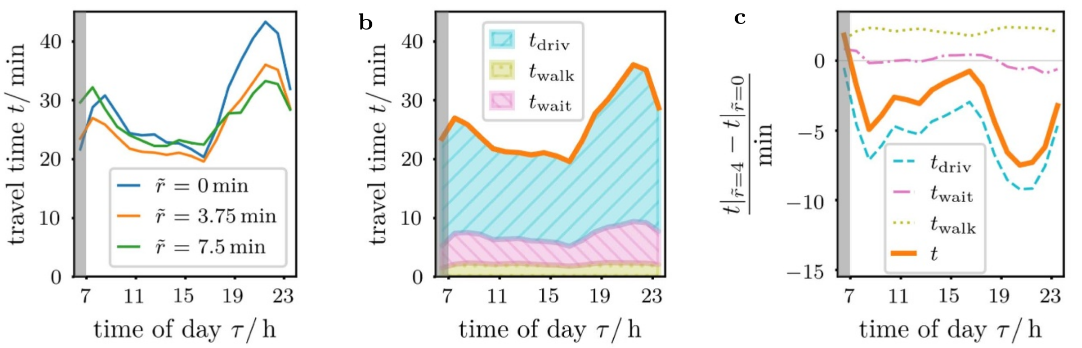

Figure 3. A fixed maximum walking distance does not use full potential at fluctuating demand. (a) The travel time t reduces with stop pooling compared to standard ride sharing (blue line), but which walk limit $\tilde{r}$ yields the shortest travel time changes across the day? Until 18:00, an intermediate walk limit $\tilde{r} = 3.75$ min yields best travel time t (orange). During the evening peak, a high walk limit $\tilde{r} = 7.5$ min yields the best travel time t (green). (b) A fixed walk limit $\tilde{r} = 3.75$ min adds an almost constant walk time t_{walk} throughout the day (light green dotted). (c) The drive time t_{driv} that fluctuates strongly with the demand (cf figure 2) reduces with stop pooling [while the wait time t_{wait} is roughly constant] such that the overall travel time t reduces (orange solid line) and fluctuates less compared to standard ride sharing (compare panel a, $\tilde{r} = 3.75$ min).

Moreover, the results demonstrate that a constant maximum walking distance does not use the full potential of stop pooling at fluctuating demand, because different maximum walking distances yield the shortest travel time t at different times of day τ. At low demand, small reductions in t_{driv} buffer only a short walk time t_{walk}. At high demand, a high reduction in t_{driv} buffers much longer walk times t_{walk}. Longer walks save more stops and are thus more efficient in reducing t. In the example, an intermediate walk limit $\tilde{r} = 3.75$ min yields the shortest travel time t before 18:00 while a high walk limit 7.5 min yields the shortest travel time t after 18:00 (figure 3(a)). Can we adapt the maximum walking distance to the instantaneous demand to increase service efficiency?

3.3. Adapting the maximum walking distances in time

To study how temporally adapting the maximum walking distance to the instantaneous global demand changes the travel times, we first perform an analysis for steady states that reveals the best suitable maximum walking distance for any given, temporally fixed demand. We realize constant demand for the steady state analysis by sampling requests from the example data set. In our analysis, the demand is represented by the product $\lambda\langle\ell\rangle$ of request rate λ and average trip length $\langle\ell\rangle$, i.e. the total travel distance requested per unit time. In the model, stop pooling reduces the travel time t at constant demand $\lambda\langle\ell\rangle$ up to some best walk limit $\tilde{r}_{\mathrm{best}}$ (figure 4(a)). A bisection method finds $\tilde{r}_{\mathrm{best}}$ for different settings with reduced computation effort (details in supplementary note 3.F.2). $\tilde{r}_{\mathrm{best}}$ increases with the demand $\lambda\langle\ell\rangle$ (figure 4(b)), because more users per bus yield more small detours that determine the potential of reduced t_{wait} and t_{driv} to buffer additional walk time t_{walk} (cf previous section). For the example setting, this increase roughly fits to a linear function,

$$\tilde{r}_{\mathrm{best}}\left(\lambda\langle\ell\rangle\right) = a\lambda\langle\ell\rangle + b, \tag{1}$$

with $a = [1.95 \pm 0.18] \times \mathrm{min\,h\,km}^{-1}$, $b = [-2.26 \pm 0.71] \times 10^4$ min and coefficient of determination [36] $R^2 = 0.92$.

Using this steady-state analysis, we suggest a simple procedure to adapt the walk limit $\tilde{r}$ to the instantaneous demand: When a user requests a trip, the global demand at the request time defines their maximum walking distance. In the example, this global walk limit $\tilde{r}_{\mathrm{glob}}$ reads

$$\tilde{r}_{\mathrm{glob}}\left(\tau_{\mathrm{request}}\right) = a\lambda\left(\tau_{\mathrm{request}}\right)\langle\ell\rangle\left(\tau_{\mathrm{request}}\right) + b. \tag{2}$$

for a user with request time τ_{request}. This global walk limit $\tilde{r}_{\mathrm{glob}}(\tau)$ varies over the day following the fluctuations of $\lambda\langle\ell\rangle$ (figure 4(c)). Again, users walk less than the walk limit $\tilde{r}_{\mathrm{glob}}(\tau)$ on average (table 1, figures 4(c) and (d)).

The global walk limit $\tilde{r}_{\mathrm{glob}}(\tau)$ yields the shortest travel times t at almost all times of day τ. Small deviations from the shortest travel time t might result from the fluctuating spatial demand patterns, because the steady state analysis uses a constant mean-field demand pattern. In the example, the travel time has a smaller mean (table 1) and fluctuates less (standard deviation 4.7 min, 19% of mean) than with standard ride sharing (6% less) or stop pooling with an intermediate fixed walk limit (2% less).

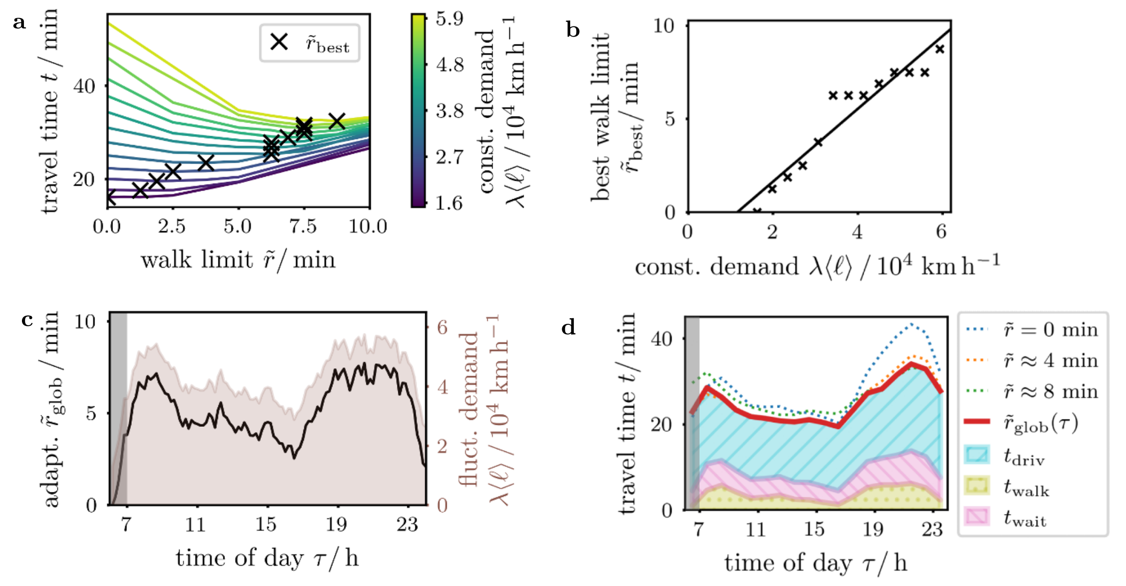

Figure 4. Temporally adapted maximum walk distance achieves consistent travel time reduction. (a) With constant demand $\lambda\langle\ell\rangle$, stop pooling reduces the travel time t up to a best walk limit $\tilde{r}_{\mathrm{best}}$ (black crosses). (b) This best walk limit $\tilde{r}_{\mathrm{best}}$ increases approximately linearly with the demand. (c) Applying the linear fit to the fluctuating demand data (brown shaded area) yields a variable walk limit $\tilde{r}_{\mathrm{glob}}(\tau)$ between 3.1 min and 7.4 min walk per stop (black line). (d) This time-adaptive stop pooling consistently achieves the shortest travel time t at almost all times of the day (thick orange line).

Table 1. Comparison of four different settings in walk time limit $\tilde{r}$, travel time t and walk time t_{walk} averaged over all time intervals (second column) and for two example time intervals (third and fourth column).

	Overall Average			16:00–17:00			21:00–22:00		
	$\frac{\tilde{r}}{\text{min}}$	$\frac{t}{\text{min}}$	$\frac{t_{\mathrm{walk}}}{\text{min}}$	$\frac{\tilde{r}}{\text{min}}$	$\frac{t}{\text{min}}$	$\frac{t_{\mathrm{walk}}}{\text{min}}$	$\frac{\tilde{r}}{\text{min}}$	$\frac{t}{\text{min}}$	$\frac{t_{\mathrm{walk}}}{\text{min}}$
No stop pooling ($\tilde{r} = 0$ min)	0.0	29.3	0.0	0.0	20.3	0.0	0.0	45.3	0.0
Static stop pooling ($\tilde{r} = 3.75$ min)	3.8	25.7	2.2	3.8	19.6	1.8	3.8	36.0	2.4
Time-adaptive stop pooling ($\tilde{r}_{\mathrm{glob}}$)	5.3	25.2	3.9	3.0	19.4	1.3	7.4	34.1	6.4
Spatio-time-adaptive stop pooling ($\tilde{r}_{\mathrm{loc}}$)	4.6	24.8	5.0	2.0	18.6	2.3	5.3	33.0	6.3

Adaptive stop pooling efficiently reduces the travel time at fluctuating demand while simultaneously reducing the travel time fluctuations. For this result it is sufficient to adapt the maximum walking distance in time. However, stop pooling is a local interaction compared to the size of a typical service region, because stops might only be pooled with nearby users. Thus, only the local demand around a user influences their efficient stop pooling setting. Typically, the local mobility demand does not only vary in time but also in space (like the taxi demand, cf figure 5(a) and [12]). For this reason, let us consider spatio-temporal demand fluctuations for adapting the maximum walking distance instead of using the global time varying demand alone.

3.4. Adapting the maximum walking distance in time and space

In principle, the local demand adaption in time *and* space could work analogous to the global adaption in time introduced above: (i) find the best walk limit for steady states in each local region (e.g. taxi zones) and (ii) adapt the maximum walking distance accordingly. However, the effort of pre-processing for each local region is very high as the region size should reflect the maximum overall acceptable walk time of a few minutes walk. We thus suggest a dynamic online adaptation according to the number of users that requested their ride in a local region of the service area. When a user i requests a trip, we count all N users j

- With origin $\mathbf{o}_j$ or destination $\mathbf{d}_j$ within a walk distance $\tilde{r}_{\max}/v_{\mathrm{u}}$ around i's origin $\mathbf{o}_i$ and destination $\mathbf{d}_i$ and
- Whose request is at most a maximum overall acceptable walk time $\tilde{r}_{\max}$ ago: $\tau_{\mathrm{request}}(i) - \tau_{\mathrm{request}}(j) < \tilde{r}_{\max}$.

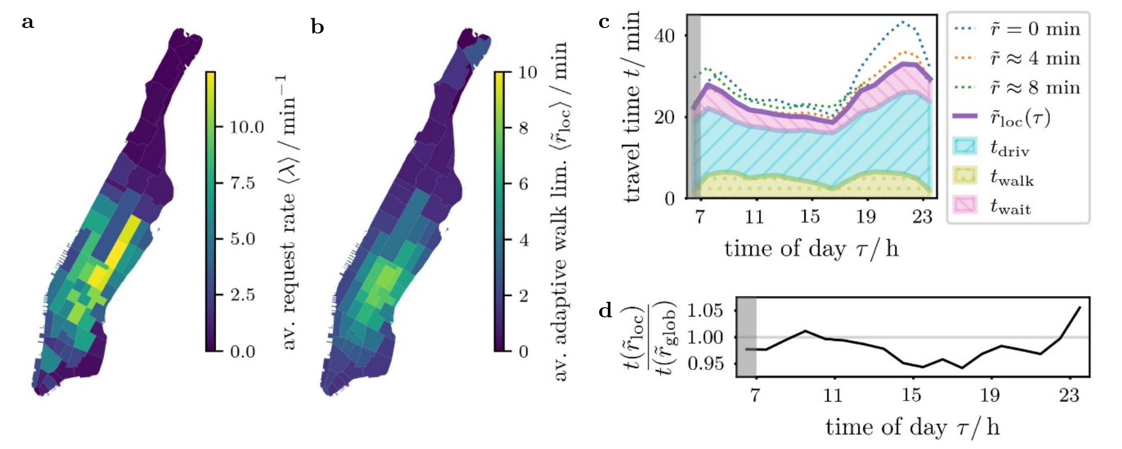

Figure 5. Spatio-temporally adapted walk limit further reduces travel times. (a) The demand is heterogeneous in space as well as in time, illustrated by the daily average request rate per taxi zone. (b) Spatially localized adaptations of the walk limit $\tilde{r}_{\rm loc}(\tau)$ only require users to walk in regions with high demand. (c), (d) With this spatio-temporally adapted walk limit, the travel time is further reduced compared to a fixed walk limit by up to 5.8% ($\hat{=}$1.5 min difference). The resulting additional walk time depends on the time of day τ (green dotted area in panel (c)).

The walk limit $\tilde{r}_{\rm loc}$ for user i depends on N and a threshold N_c:

$$\tilde{r}_{\rm loc}\left(\tau_{\rm request}\left(i\right)\right) = \begin{cases} \tilde{r}_{\max} & N(i) \geqslant N_c \\ 0 & \text{otherwise}\,. \end{cases} \tag{3}$$

When i has sufficiently many neighboring users, the walk limit is set to the maximum overall acceptable walk time $\tilde{r}_{\max}$. If not, the walk limit is set to zero. The user i might only walk with sufficiently many neighboring users to potentially pool a stop with, but almost never needs to walk the full distance since a suitable stop is likely to be closer. For the example setting, we define $\tilde{r}_{\max} = 10$ min (also used for the iterative optimization of $\tilde{r}_{\rm best} \in [0, \tilde{r}_{\max}]$). A threshold $N_c = 1000$ yields best results.

With this simple adaption scheme, the users walk only in the regions and during times of high demand (figures 5(a) and (b)), cf supplementary note 3.G, figure S11). The adaption scheme avoids that users walk in sparse demand regions while all other users are allowed to walk a maximum acceptable walk limit $\tilde{r}_{\max}$. In practice, the stop pooling algorithm determines how far each user walks, often much shorter than $\tilde{r}_{\max}$ (table 1, figure 5(c). Users walk on average longer than $\tilde{r}$ (maximum is $2\tilde{r}$—once at origin and once at destination) and longer than with exclusive temporal adaption (table 1). Nonetheless, spatio-temporal adaptive stop pooling reduces the travel time t even more than stop pooling with exclusive temporal adaption (table 1, figures 5(c) and (d)). In the example, it yields on average 1.5% and at most 5.8% smaller travel times t (cf figures 5(c) and (d)). The mean travel time is smaller than with a global walk limit $\tilde{r}_{\rm glob}$, with standard ride sharing, $\tilde{r} = 0$, or with intermediate fixed walk limit, $\tilde{r} = 3.75$ min,

$$\langle t\rangle\left(\tilde{r}_{\rm loc}\right) < \langle t\rangle\left(\tilde{r}_{\rm glob}\right) < \langle t\rangle\left(\tilde{r} = 3.75\text{ min}\right) < \langle t\rangle\left(\tilde{r} = 0\right)\,. \tag{4}$$

In the example, the spatio-temporal adaption yields on average 13.4% and at most 24.7% smaller t compared to standard ride sharing. Moreover, the travel time fluctuates less (standard deviation 4.8 min, 19.5% of mean) than with standard ride sharing or stop pooling with intermediate fixed walk limit, $\tilde{r} = 3.75$ min. A user who requests a ride between 21:00 and 22:00 travels on average less than twice as much than users who requests a ride between 16:00 and 17:00 (table 1). The fluctuations are slightly higher than with a global walk limit $\tilde{r}_{\rm glob}$. Still, adaptive stop pooling efficiently reduces the travel time at fluctuating demand while simultaneously reducing the travel time fluctuations.

All in all, stop pooling reduces fluctuations of the average travel time of ride sharing users at a constant fleet size. In the given example, this is true no matter if the walk limit is adapted in time or in time and space or not at all (figure 6(b)). In addition, stop pooling consistently reduces the travel time when the maximum walking distance is adapted to the instantaneous demand. In the example, a spatio-temporal adaption yields a slightly higher reduction of the travel time than a purely temporal adaption (figure 6(a)).

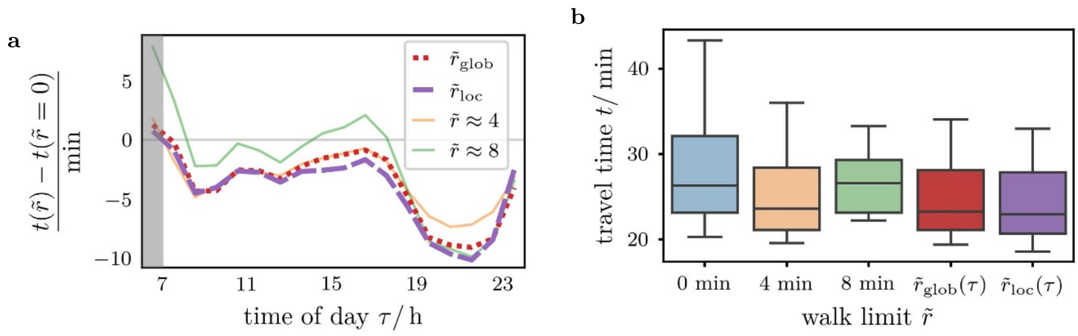

Figure 6. Stop pooling reduces travel time and travel time fluctuations. (a) Adaptive stop pooling significantly reduces the travel time compared to standard ride sharing. The effect is larger when travel times are high, e.g. during high demand in the evening. Local adaptation of the walk limit $\tilde{r}_{\text{loc}}$ further improves travel time saving. (b) With stop pooling, the travel time fluctuates less. The mean travel time t (horizontal bar) is smaller with adapted $\tilde{r}_{\text{glob}}$ and $\tilde{r}_{\text{loc}}$ than with a fixed walk limit $\tilde{r}$. The local walk limit $\tilde{r}_{\text{loc}}$ yields the smallest mean t. Furthermore, the averages of t in one-hour-intervals spread in a smaller range with adapted $\tilde{r}_{\text{glob}}$ and $\tilde{r}_{\text{loc}}$ than with standard ride sharing $\tilde{r}=0$, making ride sharing travel times more reliable.

4. Discussion

Ride sharing users might experience unreliable, highly fluctuating travel times over the day induced by fluctuating demand. We here propose to reduce these travel time fluctuations by adaptive stop pooling, requiring some users to walk a short distance and pool their stops with other users. Interestingly, some ride sharing services already include short walks from exact locations to close-by virtual bus stops [37–41]. Instead of sending users to the closest virtual bus stop, the proposed stop pooling scheme combines user stops flexibly, which might be particularly efficient when adapting the maximum walking distance to the current demand.

In this article, we study the qualitative collective influence of stop pooling in basic models of ride sharing fleets operating at fluctuating demand using event-based simulations. We find that stop pooling may reduce the user travel time, because buses drive along more direct routes. The reduction is larger the higher the travel time initially. Consequently, stop pooling also reduces travel time fluctuations. The optimal maximum walking distance depends on the demand: Users should walk further for higher demand, where higher time savings buffer higher walk times. We demonstrate this with two example procedures of adaptive stop pooling adjusting the maximum walking distance to the current demand: (i) setting the maximum walking distance to the best suitable distance for the current global demand or (ii) deciding if a user walks or not based on the local demand around the user. With both procedures, the travel time is on average smaller and fluctuates less than with standard ride sharing.

In general, ride sharing operators have different options to suitably design their service to adapt to fluctuating demand. A common strategy is to adapt the fleet size [10, 14] requiring to provide additional vehicles and drivers which increases the overall carbon emissions and costs of the ride sharing system. Alternatively, providers may adapt their dispatcher which requires less effort and allows finer and faster adaptation. For instance, dynamic pricing [42, 43] might increase the user incentive for sharing trips [44] if necessary, but dynamic pricing has already been misused by drivers to artificially increase the cost for a ride [45]. As demonstrated above, adaptive stop pooling requires only a straightforward adaption of the dispatcher, without requiring additional or higher-capacity vehicles (details in supplementary note 3.G, figure S12). Adaptive stop pooling may thus contribute to cheap and sustainable ride sharing with reliable travel times.

Our analysis has focused on qualitative effects of adaptive stop pooling. The quantitative results depend on parameters like fleet size or vehicle velocity (supplementary note 4.H) and should be seen as examples. For instance, the model uses a constant mean-field velocity. Typically, vehicle velocities reduce during times of high demand (rush hour), further contributing to high travel times. However, stop pooling reduces travel times more strongly compared to standard ride sharing when the difference between driving and walking velocity is smaller, since longer walk times are possible (see supplementary note 4.H). Consequently, we expect the potential of stop pooling to reduce variability of travel times across the day to remain robust. Moreover, the model uses a simple assignment algorithm, but we show that the result is robust for a more complex algorithm (supplementary note 4.I citing [46–55]): When limiting the user travel time by a maximal delay, providers have to reject users if the demand exceeds the supply. Then, the rate of rejected users fluctuates instead of the travel time and adaptive stop pooling reduces the fluctuations of the rejection rate. Besides, the model does not include that short user walks might reduce the perceived service quality. In general, walk time is typically valued less than waiting for or driving in the vehicle [56], walking might provoke safety risks (especially at night) and walking might not even be possible for some users. However, stop pooling requires only some users walk while others are served from door to door. Further research questions result from the suggested methods to adapt the maximum walking distance to current demand. For example one might avoid repeated pre-processing when discovering universal scaling laws either for the best maximum walking distance or for the optimal minimum number of neighbors to pool stops with. We found this threshold by trial and error, but results are robust for slight deviations $N_c \in [750, 1250]$. In addition, one may further develop the adaption methods themselves. For example, the spatio-temporal adaption might improve by differentiating between the local demand around the origin and that around the destination of a user, or by taking the age of stops into account.

The results in this article contribute to a fundamental understanding of the collective dynamics of ride sharing systems under conditions of fluctuating demand. Moreover, the results might motivate (i) ride sharing providers to include stop pooling into their service, because the service may become more efficient, and (ii) users to participate in a stop pooling service, because their total travel time may—counterintuitively—decrease. The presented basic stop pooling algorithm that includes two procedures to adapt the maximum walking distance to the current demand might serve as a basis for future adaptive dispatchers. Such ride sharing services including adaptive stop pooling may contribute to sustainable and reliable human mobility.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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C L: Conceptualization, literature review, modeling, simulation code, simulations and data analysis, manuscript writing, and editing. P M: Modeling and simulation code. M S: Conceptualization, modeling, supervising simulations, data interpretation, manuscript writing, and editing. M T: Conceptualization, data analysis, manuscript writing, and editing.

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