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Travel demand management: the solution to public transit congestion?

An ex-ante evaluation of staggered work hours schemes for the Paris region

Nicolas Coulombel[1,], Emmanuel Munch[1], Cyril Pivano[2]*

Abstract

This paper investigates the congestion relief potential of staggered work hours (SWH) schemes for public transit lines. An ex-ante evaluation framework is developed, building on the combination of a hybrid public transit assignment model with a travel demand management module to simulate the impact of SWH schemes on travel demand and public transit congestion. The key performance indicators capture not only congestion relief benefits, but also rescheduling costs for users. The methodology is applied to the RER A heavy rail line in Paris, the busiest public transit line in Europe. We find SWH schemes to entail congestion relief benefits, as intended, even matching up with telework policies (in that shifting one peak trip produces benefits equivalent to cancelling one morning trip). Yet, such benefits remain limited, adding up to around 20% of total crowding costs for the morning peak period at most. Furthermore, substantial rescheduling costs are involved: decreasing the total time standing by one hour implies shifting fifteen trips also by one hour. Regarding design, we find that shifting few users by a large amount of time is usually more efficient than shifting many users by a shorter amount of time, as the latter may even prove counterproductive by just moving the peak to some other time in the morning. Moreover, we find that focusing the deployment of the SWH scheme on the biggest trip attractor – here the CBD station of La Défense - yields results similar to a deployment over the whole line (for a similar total timeshift). The developed ex-ante evaluation framework could therefore provide guidance as how to improve the design of SWH schemes in the future, in particular in times of social distancing and need for reduced crowding.

Keywords: public transit; congestion; travel demand management; staggered work hours; telework

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1 Introduction

While public transportation remains to date the cornerstone of sustainable urban mobility, more and more cities must deal with increasingly congested transit networks (Yang and Tang, 2018). Yet congestion is the source of many economic inefficiencies (Haywood et al., 2017; Tirachini et al., 2013). In addition to degrading users' travel conditions (time spent in congestion, discomfort…), it may affect the activities following or preceding their trip (delay to a meeting, early departure from home/work, productivity loss due to anxiety...), thus the economic sphere as a whole. Congestion also affects operations through delays and lower service reliability, resulting in extra costs for the operator.

Considering the limits of supply-side solutions,[2] the focus has shifted on how to optimize the use of the existing network through Travel Demand Management (TDM). Following the Avoid-Shift-Improve (ASI) typology (as in e.g. Nakamura and Hayashi, 2013), TDM policies can be schematically classified into those that aim A) to reduce distances travelled, S) to shift trips in time or in space in order to make better use of the available transit capacity, and I) to improve the efficiency of the public transit system. Telework (Zhang et al., 2005) is the epitome of the Avoid category. Improve policies include transit operations control (Daganzo, 2009; Schmöcker et al., 2016), passenger flow control (Xu et al., 2016), and combinations of both (Liu et al., 2020). Within the Shift category, congestion pricing has attracted considerable attention since Vickrey's seminal works (Vickrey, 1973, 1969). In the case of public transit, examples of application include peak-fare charging such as in Taipei, Washington D.C and London, and off-peak discounting as in Melbourne (Yang and Tang, 2018). Yet cases of implementation remain rare, because of the technical complexity involved (though substantially lower for public transit than for road travel), or of the unpopularity and social inequity of such policies (De Borger and Proost, 2012; Vanoutrive and Zijlstra, 2018). As shown by Henderson (1981), an alternative to achieve a similar result is to stagger work hours. Staggered work/school hours (SWH) schemes seem relatively easy to implement and inexpensive to boot, resulting in renewed interest and applications in cities over the world (Briand et al., 2017; Zong et al., 2013).[3] In contrast to a large theoretical literature (reviewed recently in Takayama, 2015), empirical works remain scarce to date, especially regarding how to design the SWH scheme. Questions such as how many trips should be shifted, when (before or after the peak),

[2] To meet increasing public transit demand, supply-side solutions include increasing service frequency and vehicle capacity in the short and medium run (Mohring, 1972; Tirachini et al., 2010), or line density in the longer run (Fielbaum et al., 2020). Yet, improving service quality can only efficiently accommodate increasing travel demand up to a certain extent (Coulombel and Monchambert, 2020). Expanding the network is for its part costly, requires land, an increasingly scarce resource in denser cities, and might even ultimately be counterproductive in the long run by stimulating induced demand (as documented by Duranton and Turner, 2011, in the case of road travel).

[3] SWH schemes do not present any technical difficulties, mostly coordination within and across firms/schools. Therefore, they require virtually no material investment, only preparation and training meetings.

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and by how much time, are seldom if at all addressed in the literature. The literature has also largely focused on road travel as yet, with limited attention to public transit.

This work aims to fill this gap by developing an ex-ante evaluation framework of staggered work hour schemes for a mass transit line and by applying it to the RER A, Paris. We are especially interested in how the design of the SWH scheme influences its performance, with a focus on in-vehicle comfort. Key design parameters include the proportion of trips shifted, the direction and magnitude of the shift, and the selected target (single station vs. deployment over the whole transit line). The corresponding SWH scheme is then evaluated using Key Performance Indicators derived from a hybrid public transit assignment model. The hybrid model allows us to capture the effects of SWH schemes on several congestion mechanisms that are specific to public transit: seating availability, in-vehicle crowding, denied boarding. Two types of schemes are considered: centralized scenarios cap the departure rate by perfectly coordinating user departure times, while decentralized scenarios intend to emulate more realistic SWH schemes by applying simpler rules at the individual level (e.g. make x% of peak users leave 1h earlier). The methodology is applied to the RER A heavy rail line in Paris. With more than 1.2 million passengers per day, it is the most used urban transportation line in Europe, therefore facing recurrent crowding issues. Frequency and vehicle capacity having been raised to the maximum - with 27 trains/h at peak hour, each with a carriage capacity of 2,600 users – the RER A is a prime candidate for SWH schemes.[4]

We find that SWH schemes do achieve their intended purpose, as expected: they smooth the peak and better distribute RER A users across vehicles, thus improving in-vehicle comfort. Yet not all users see their travel experience improve. Considering that SWH policies move a fraction of peak users to the off-peak period, “peak stayers” benefit the most from such policies by enjoying lower congestion at no rescheduling cost. Off-peak users experience on the other hand greater congestion than before. More unexpectedly, we find out that for a similar total timeshift (number of trips shifted x mean shift), decentralized schemes often perform better than centralized ones, implying that it is usually more efficient to shift few users by a large amount of time than many users by a shorter amount of time. Centralized schemes are robust to upscaling, however, whereas large decentralized schemes tend to yield counterproductive results by just transferring the peak at some other time in the morning. Similarly, while the “delay only” strategy proves more efficient at first by leveraging the larger residual capacity after the peak, the balanced “delay and advance” strategy performs better at larger scales.

[4] As a matter of fact the transit authority and the operators of the RER A have initiated in 2019 on these exact grounds a small-scale SWH experiment with the firms of the CBD of La Défense (Région Île-de-France, 2018).

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Relatively to the spatial design, we find out that targeting the station of La Défense (first trip generator for the RER A) yields results similar to a deployment over the whole line.

The analysis of the efficiency of SWH policies leads to mixed results. On the one hand we note that they perform well compared to telework: shifting one peak trip (arrival between 8.30 am and 9.30 am) has an effect similar to cancelling one morning trip (from 6 am to 11 am) regarding crowding costs. However, the decentralized SWH schemes tested here only manage to abate crowding costs by around 20% at most, while involving substantial rescheduling costs. Decreasing the total time standing by one hour implies shifting fifteen trips by the same amount of time. Alternatively, we observe that for SWH schemes to yield positive benefits the long term rescheduling shadow price must be lower than one tenth the VTTS, which seems unrealistically low. All in all, SWH schemes could be used to mitigate congestion in the RER A to some extent, yet at substantial rescheduling costs. In the longer run, because there are just too many users in the RER A, very large scale centralized SWH schemes or alternative Avoid and Shift TDM policies (e.g. telework, congestion pricing) would ultimately be needed to substantially reduce crowding.

This paper contributes to the literature by developing an ex-ante evaluation framework in the case of SWH schemes for public transit. The benefits in terms of congestion relief (measured by the total time standing or crowding cost savings) are balanced with the rescheduling costs (proxied by the total timeshift in absence of valuation for changes in work start times). This contrasts with previous works which focus on road travel and travel time variations, seldom considering the cost of TDM measures. This work is also the first (to the best of our knowledge) to apply a hybrid public transit assignment model to evaluate SWH schemes, which allows us to capture the congestion relief benefits with regard to several forms of public transit congestion: seat availability, in-vehicle crowding and denied boarding. Finally, this work also provides recommendations for the design of SWH schemes for the RER A. Several alternative working schedules have failed in the past as they were launched as experiments, with minimal communication on the benefits or the costs to be expected, resulting in low acceptability and adoption by the firms (Munch, 2014; O'Malley, 1974). By providing objective measures of costs and benefits, this ex-ante evaluation framework is intended to help designing and communicating SWH schemes, and thus to improve their acceptability in the future. In the context of social distancing due to the Covid-19 epidemic, this seems all the more pressing as many countries and cities around the world rely on TDM and firstly on telework and SWH schemes to limit user density in public transit during peak-hour (e.g. Philippe, 2020 in the case of France) .

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2 Literature review

The literature on the evaluation of staggered work hours' schemes can be classified into three strands: theoretical works, ex-post evaluations (based on observed data) and ex-ante evaluations (based on simulation).

2.1 Theoretical works

While local agencies have started considering staggered work hours schemes as early as in the 1920s, later proceeding to first formal experiments in the 1950s (Maric, 1978), the first theoretical work to analyze these policies only dates to the 1980s. In his seminal paper, Henderson (1981) develops a model which capture three main features of SWH schemes, namely their effect on: 1) travel conditions, 2) home schedule and 3) work productivity. Travel conditions are modeled in a simple fashion using a general travel time function. Schedule preferences are represented through an ideal work start time $\bar{s}$ that captures general preferences such as working in daytime rather than at nighttime or constraints such as dropping the children to school, and a consecutive opportunity cost of working time $C(s - \bar{s})$. Work productivity is captured through an instantaneous production function which depends on the number of workers present at a given time. When choosing when to depart, users make a trade-off between leaving at their ideal departure and experiencing heavy congestion, or leaving earlier or later in order to save travel time but at a greater scheduling cost. This results in departures being spread at equilibrium, implying that there is a latent demand from users for SWH schemes. But Henderson also shows that the optimal departure profile is even flatter and more spread than the equilibrium one, and that it can be achieved either using congestion pricing (as expected), or more innovatively by taxing work start times.

Following Henderson (1981), the (sizable) theoretical literature has progressed into two directions: improving the representation of the transportation technology using Vickrey's bottleneck model (Takayama, 2015; Zhang et al., 2005; Zhu et al., 2019), and the representation of agglomeration effects (Arnott, 2007; Arnott et al., 2005; Fosgerau and Small, 2014; Mun and Yonekawa, 2006; Wilson, 1992). All in all, all works naturally conclude that because spending time in congestion is a deadweight loss, one should seek to smooth and cap the users' departure rate in accordance with the outflow capacity of the infrastructure in order to reach the optimum. This may be achieved by using SWH schemes, congestion pricing, or a combination of both. Yet the specific case of public transit with its specificities (crowding, discrete departures…) is seldom addressed in the theoretical literature.

2.2 Ex-post evaluations

The use of staggered work hours schemes as a transportation policy has a relatively long history (Munch, 2014). As soon as in 1950s and 1960s, citywide scale experiments were initiated in England

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and in France. Yet these were not as successful as expected, partly because they were heavily focused on optimizing the city's economic functions and public transit networks, and were far removed from the concerns of employers and employees.

Few years later, Alternative Work Schedules (AWS) applied to road traffic were trialed in a number of American cities. One of the first experiments was launched in 1973 in New York by the Downtown Lower Manhattan Association and the Port Authority of New York and New Jersey. This major program involved 220,000 employees from 400 different companies, but unfortunately its terms and its effects were poorly documented (O'Malley, 1974). In 1998 a SWH program was implemented in Honolulu, involving 4,000 employees (7% of the downtown work force). For the first time this SWH program was precisely evaluated. About half the state, county and city employees had to move their official work hours from 7:45 a.m. to 4:30 p.m. to 8:30 a.m. to 5:15 p.m., while 8.4% of employees did the same in the private sector. Peak travel time was reduced by 8% on average in Honolulu, and even up to 18% depending on the route that commuters took (Giuliano and Golob, 1990). The program rose equity concerns however, as non-participants were found to benefit more than participants.

In Europe, time offices were created at the beginning of the 1990s to face, among other things, the potential inequity of such measures (Bonfiglioli, 1997). Those aim to design more satisfactory day-to-day schedules in urban areas through citizen participation. In terms of travel demand management during the peak period, local operations have focused on the staggering of lecture schedules to spread morning commuter flows in public transit. In France, since 2000 the cities of, Poitiers, Montpellier and Rennes have negotiated agreements with transit operators and universities to shift part of the first morning lectures from 15 to 30 minutes, with promising results to date. In Rennes, the subway operator was able to avoid (or at least delay) a planned investment of €12 million to purchase three additional trains, while users enjoyed less cases of overcrowded trains with an average 17% decrease of the load factor during the morning 8:00 am – 8:15 am hyperpeak (Briand et al., 2017). Urban time policies applied to school or university schedules are also being implemented in other countries such as Australia (Daniels and Mulley, 2012) and England also in line with health and academic performance concerns (Kelley et al., 2017). Still, SWH schemes for firms remain a popular policy in several countries. In China, those have achieved good effects in several major cities, with for instance a 30% reduction of morning peak traffic in Jinan (Zong et al., 2013, Table 1).

2.3 Ex-ante evaluations

While the ex-post evaluations presented above investigate the actual benefits of SWH programs, to the best of our knowledge none provides estimates of expected benefits that could serve as a reference to evaluate the efficiency of the program. Ex-ante evaluations are useful in defining such

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prior estimates, as well as in supporting decision-makers in the specific design of the SWH policy (as ex-post evaluations only provide fairly limited guidance in this regard).

In this direction, Guo and Srinivasan (2005) develop a road traffic model that captures day-to-day dynamics and the effects of users' switches in route and departure time due to information provision, experience and learning mechanisms, and several TDM policies including SWH schemes. The authors find TDM policies and especially SWH schemes to yield promising results in reducing peak travel time, but also in improving travel time reliability. Yet the brief evaluation of TDM schemes is more intended at demonstrating the capacities of the model, considers only benefits, and only travel time indicators. Zong et al. (2013) carry out a more systematic evaluation of SWH schemes in the case of Beijing, China. Using the combination of a departure time choice multinomial logit model and of a hazard duration model for travel times, the authors evaluate the effects of four different SWH schemes on travel times. They find that by shifting the work start time of government and service industries to 9:00 a.m. instead of 8.30 a.m. (program B), traffic volumes between 6:30 a.m. and 8:30 a.m. are reduced by 15.24%, whereas home-to-work travel time decreases by 21.73%. Again, the SWH programs are only evaluated through the lens of travel times, however, with no consideration to rescheduling costs.

Based on this review, this paper seeks to extend the literature on the ex-ante evaluation - and more generally on the evaluation - of staggered work hours' programs through three main contributions. First, we develop an evaluation framework specific to public transit (including phenomena such as waiting, in-vehicle crowding…), which has been the object of limited attention in previous works.[5] Second, we leverage Key Performance Indicators not considered in previous works and which allow for a more comprehensive economic evaluation of SWH programs, such as generalized costs to measure congestion relief benefits and total timeshift to appraise rescheduling costs. Finally, we investigate for a real case study several design parameters of a SWH scheme, such as the number of trips to be shifted, the direction and the magnitude of the shift, and on which transit stations to deploy the SWH scheme. This leads to some unexpected results, the generality of which could be tested on other case studies in future research works.

[5] The methodological framework, which combines a data-oriented approach to estimate the dynamic O-D matrix and a dedicated hybrid line model to evaluate the performance of the various SWH schemes, has similarities with the framework developed by Li et al. (2018). The latter focus on the evaluation of off-peak discount schemes, however, and does not propose several of the KPI developed here such as crowding and scheduling costs.

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3 Methodology

3.1 General framework

This paper investigates to what extent travel demand management (TDM) measures – with a focus on staggered work/school hours, and to a lesser extent telework – can alleviate congestion in the case of a strongly used transit line, namely the RER A in the following case study. The relative performance of the TDM scenarios with respect to the reference scenario is evaluated using a combination of several Key Performance Indicators (KPI) presented in subsection**Erreur ! Source du renvoi introuvable.Erreur ! Source du renvoi introuvable.** 3.4, which are computed using a 3-step methodology (**Erreur ! Source du renvoi introuvable.**).

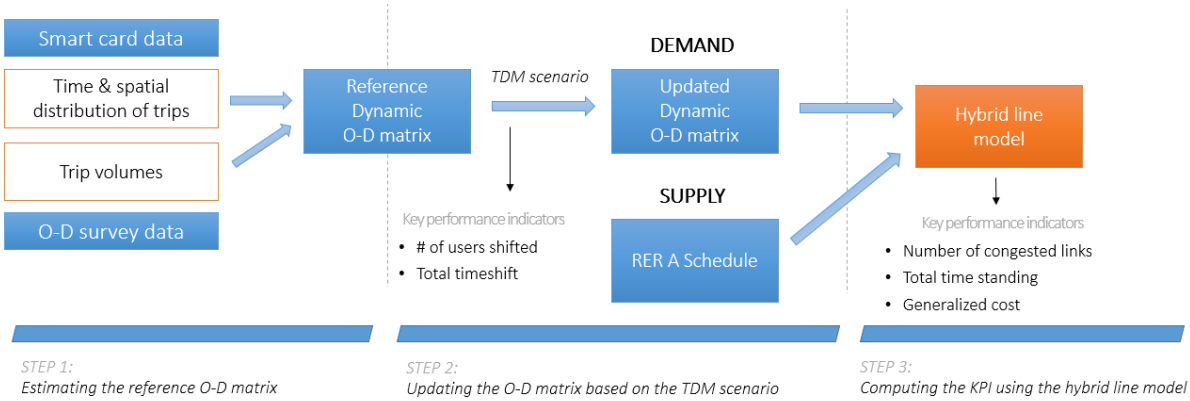

Figure 1. Methodological framework

The first step aims to estimate a dynamic O-D matrix for the reference scenario, by combining two datasets: AFC data and an origin-destination survey (presented in subsection 3.2). The AFC data is used to determine the basic structure of the dynamic O-D matrix, building on the information about transit legs available at the individual level. However, the AFC dataset has limitations both regarding its scope (paper tickets used by non-regular travelers are not included in the dataset) as well as within its scope (e.g. non-validations or data collection issues). The O-D survey is therefore used to rescale the raw AFC O-D matrix to reproduce consistent trip volumes.

Next in the second step, the reference dynamic O-D matrix generated in the first step is updated to simulate the TDM scenarios by applying the corresponding rules (see subsection 3.3).

In the final step, the usage of the transit line and the KPI assessing the performance of the TDM scenarios are computed using the hybrid line model (Poulhès et al., 2017), which can then be used to calculate some on-board comfort indicators (Leurent, 2009). The hybrid line model combines a macroscopic representation of passenger flows with a microscopic simulation of vehicles to derive user-oriented indicators (waiting time, in-vehicle travel time, generalized cost), as well as transit line indicators (vehicle load ratios, line-haul travel times) for each vehicle and each interstation. The hybrid

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line model considers vehicle capacity and several forms of congestion: in-vehicle crowding, denied boardings, and on-platform congestion (longer dwelling times as the number users seeking to board and alight increases). Accordingly, TDM measures, in addition to improving in-vehicle crowding, may also result in lower travel times in the hybrid line model by reducing denied boardings and by decreasing dwelling times.

3.2 Data

To estimate the reference dynamic O-D matrix for the time period considered – being the morning period (6 am - 11 am) in the following RER A case study – two data sources are combined: Automated Fare Collection (AFC) data and an origin-destination survey.

3.2.1 AFC data

The Ile-de-France public transit network currently uses two ticketing systems: smart cards and paper tickets. As transit passes, called Navigo for commuters and Imagine R for students, are only available on smart cards,[6] the penetration rate of smart cards is very high: they represent around 80% of all trips in the public transit system.[7]

In this study we use an AFC dataset corresponding to the time period of March, 2015. The analysis focuses on Tuesday 17th of March, 2015, as representative of a busy working day with heavy congestion (public transit use being typically greater on Tuesdays and Thursdays in Paris). The AFC dataset only reports trips made by pass holders. Accordingly, two main types of trips are absent from the dataset: those made using paper tickets, and those for which the user did not tap his smart card, whatever the reason may be (including fraud). The RER A is a tap in/tap out system, meaning that both the origin and destination of the transit leg are usually reported in the dataset. In case of connections with other lines of the RER network, the transfer does not require tapping the smart card, in which case either the origin or the destination is missing (amounting to 18% of trips in our dataset). The missing origin or destination may usually easily be inferred, however, by tracking the entry point and the exit point of the user on the RER network, allowing to determine which line was used before or after the RER A, and where the connection took place.

[6] In addition to unlimited travel passes, digital tickets are also available on smart cards for less frequent users.
[7] Source: https://www.iledefrance-mobilites.fr/usages-et-usagers-des-titres-de-transport

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3.2.2 The TJRF origin-destination survey

The Rail Network Daily Traffic (*Trafic Journalier du Réseau Ferré* or TJRF in French) is a survey carried out by the RATP – the primary operator of the RER A[8] - since 1997. Consisting of 300,000 interviews, the survey covers 72,000 different origin-destination routes for the urban rail network (totaling around 6 million trips per day).

We use the 2015 dataset, which provides for each observation:

- the station and time of boarding;
- the station and time of alighting;
- a weight aiming to correctly reproduce the observed mean traffic volumes, and which is estimated by the RATP using passenger count data.

The TJRF dataset allows us to rescale the raw AFC O-D matrix to reproduce traffic volumes which are consistent with the observed situation for 2015.

3.3 Scenarios

Two types of travel demand management scenarios are considered: centralized then decentralized. The former intends to represent an optimal spreading of departures (for a target maximum departure rate during the peak), while the latter intend to represent more realistic measures, which can be implemented through simple rules at the individual level.

3.3.1 Centralized scenarios

The first category of scenarios corresponds to a situation in which part of peak trips are shifted before and after the peak hour to cap the departure rate at a given target maximum level (**Erreur ! Source du renvoi introuvable.**). This intends to make the departure rate curve closer to the optimum, which from the survey of the theoretical literature (see subsection 2.1) is flattened in accordance with the infrastructure capacity. The maximum departure level then allows to adjust the maximum crowding level aimed for by the SWH scheme: the lower the maximum departure rate, the lower the maximum crowding level will be. The scenarios are parametrized by three features: the maximum departure rate over the transit line (in users/min), the fraction of trips to be shifted earlier (as opposed to being shifted after the peak), and the extension of the peak hour period (defined here as the period with user departure rates at or above the chosen maximum threshold). For ease of understanding, the last two parameters will remain constant throughout the analysis at some given "best practice" values learnt from sensitivity analysis. This allows us to focus on the effect of the first parameter, the

[8] The RER A is actually operated by two operators: the RATP and the SNCF. The RATP operates the largest part of the RER A, however, including the central section between Vincennes and Nanterre Préfecture which features the highest levels of congestion.

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maximum departure rate level, which is easier to interpret and is related to the scale (or intensity) of the SWH program: as the threshold is set lower and lower, more and more trips have to be shifted in order to meet the maximum departure rate constraint.

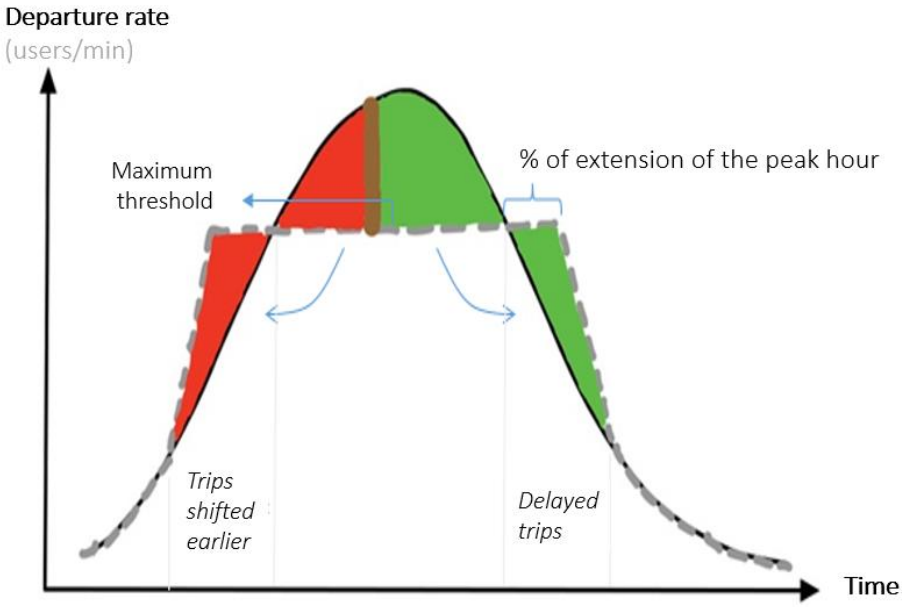

Figure 2 : Schematic representation of the centralized TDM scenarios

This "ideal" peak spreading scheme involves shifting trips in a relatively complex manner: some trips are moved earlier by a small time shift, while for others the time shift may be more substantial. This means that centralized scenarios can indeed only be achieved by means of some centralized procedure (such as a mobile app giving detailed personalized instructions to each user).

3.3.2 Decentralized scenarios

Because this first category of scenarios is rather theoretical (at least for now), the second category of scenarios intends to describe situations in which a share of peak users of the public transit line are encouraged to advance or delay their trip based on simpler rules such as:

- "delay and advance" strategy: if you usually leave during the rush hour between t_0 and t_1, depart *X* minutes earlier or *Y* minutes later (**Erreur ! Source du renvoi introuvable.**);
- "delay only" strategy: depart *Y* minutes later if you usually leave between t_0 and t_1;
- same rules as above but based on arrival times.

In the case of scenarios based on user arrival times, the latter are estimated from the reference O-D matrix by considering average travel times for the period considered (to account for the longer travel times during the morning peak). To arrive 60 minutes later, one would usually expect the user to depart 60 minutes later, but that is true only if the travel time is constant. Because of congestion, the user may departs only 50 minutes later if congestion increases so that the user must takes an extra safety

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margin, or conversely 70 minutes later if congestion decreases so that by shifting his trip the user enjoys lower travel times.

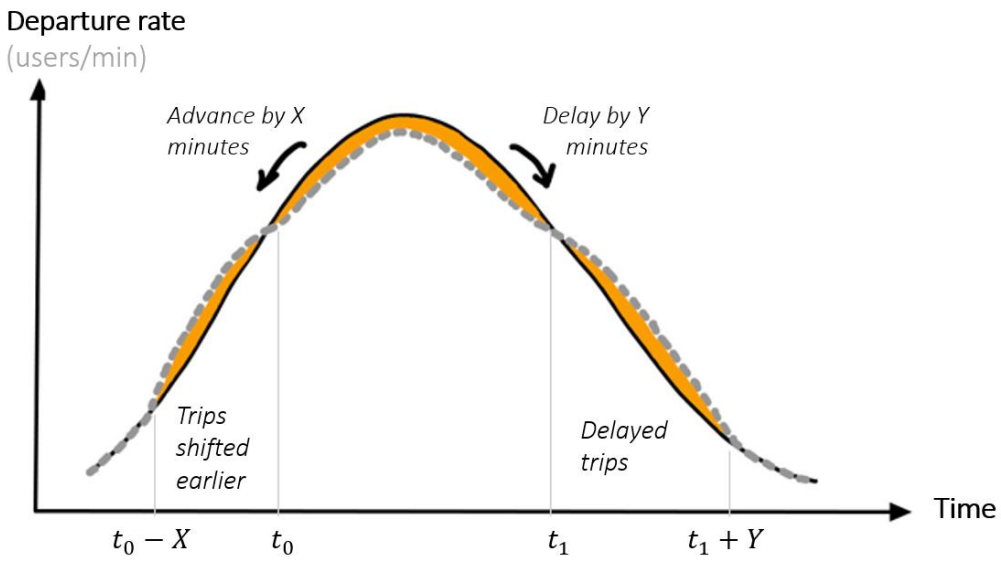

Figure 3 : Schematic representation of the "delay and advance" decentralized TDM scenarios

The scenarios may be applied to either all users, or only users departing or arriving at a specific station. For instance, a TDM scenario based on arrival times at a given station corresponds to a situation in which firms (or school/universities) around the station would enforce a staggered work hours' scheme. As a matter of fact, there are reasons to expect that focusing on the main traffic generators could improve the efficiency of SWH schemes (Hines, 1982; Munch, 2014).

3.4 Hybrid public transit assignment model

Once the O-D matrix modified by the TDM module, it used as input data in the hybrid line model. First, a "flowing model" simulates boarding and alighting of passengers for each station and vehicle. This allows us to know the volume of passengers on each link. Then, a comfort model is used to derive the seating or standing status of passengers, and the resulting generalized cost of travel. We briefly describe the flowing model and the comfort model below, and refer the reader to model Poulhès et al. (2017) and Leurent (2009) for more details.

3.4.1 Vehicle load

The hybrid line model considers mission sequencing and capacity constraints, i.e. some passengers may pass a vehicle because it does not serve the desired destinations or because it is overloaded.

Consider a vehicle *k* arriving at station *r*. Residual capacity before entering the station is denoted by $\kappa_k^{(r)}$. The number of users who are onboard and willing to alight at stations $s \geq r$ is denoted by $y_{k,s}^{(r)}$.

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If the vehicle stops at station r, the $y_{k,r}^{(r)}$ passengers in the vehicle bound for this station get off. This frees up space in the vehicle, resulting in the following residual capacity for boarding passengers:

$$\bar{\kappa}_k^{(r)} = \kappa_k^{(r)} + y_{k,r}^{(r)}.$$

The time available for boarding $\bar{\omega}_k^{(r)}$ is the total dwelling time $\omega_k^{(r)}$ minus the passenger alighting time: $\bar{\omega}_k^{(r)} = \left(\omega_k^{(r)} - y_{k,r}^{(r)}\theta_k^- / u_k\right)^+$, where θ_k^- is the unit alighting time for vehicle k and u_k the number of openings. The corresponding boarding capacity is thus $\bar{\omega}_k^{(r)} u_k / \theta_k^+$, where θ_k^+ is the unit boarding time. Factoring also the residual capacity, the actual capacity available for boarding candidates is:

$$\hat{\kappa}_k^{(r)} = \min\{\bar{\kappa}_k^{(r)}, \bar{\omega}_k^{(r)} u_k / \theta_k^+\}$$

The cumulated passengers having entered the line at station r and bound for station s at the time vehicle k enters station r is denoted by $X_{r,s}^+(k)$. It is derived from the (modified) O-D matrix. The number of boarding candidates is then simply the difference between the cumulated passengers when vehicle k arrives and the cumulated passengers $X_{r,s}^-(\lambda_{r,s}(k))$ who managed to board at the time of the previous vehicle $\lambda_{rs}(k)$:

$$B_r^k = \sum_{s \in S_k, s > r} X_{r,s}^+(k) - X_{r,s}^-(\lambda_{r,s}(k)).$$

If $B_r^k \leq \hat{\kappa}_k^{(r)}$ then all candidates can board. Otherwise, some passengers must wait for another vehicle. A FIFO priority rule is postulated: passengers who arrived first board first. This is modeled by keeping track of "passenger waves" that arrived at the station during the respective headways of previous runs. The "active wave" of leg (r, s) is the first one for which there are still boarding candidates waiting up to run k. Let us denote it by $l_{r,s}^{(k)}$. The wave indices are taken in the full set of runs, since the priority rule holds both between the passengers with a given destination and between the different destinations. From the oldest active wave $l_{r,k}^* = \min\{l_{r,s}^{(k)} : s \in S_k, s > r\}$, let us compute the number of candidates stemming from the currently active waves $l \in l_{r,k}^*, \dots, k$ in a cumulative way:

$$V_{r,k}^{(l)} = \sum_{s \in S_k, s > r} X_{r,s}^+(k) - X_{rs}^-(\lambda_{rs}(k)).$$

Now, if $V_{r,k}^{(l)} \leq \hat{\kappa}_k^{(r)}$ then all candidates can board. Following consequences must be derived.

$$\forall s \in S_k,\ s > r:\ \ell_{rs}^{(\mu_{rs}(k))} = k,\ \hat{y}_{rs}^{(k)} = X_{rs}^+(k) - X_{rs}^-(\lambda_{rs}(k)) \text{ and } X_{rs}^-(k) = X_{r,s}^+(k).$$

Otherwise, $V_{r,k}^{(k)} > \hat{\kappa}_k^{(r)}$ let $\hat{\ell}$ be the first wave such that $V_{r,k}^{(\ell)} > \hat{\kappa}_k^{(r)}$. Passengers up to $\hat{\ell} - 1$ can board in k, as can part of the $\hat{\ell}$-th wave only. While the rest of boarding candidates must wait for posterior vehicles. The restriction factor wave $\hat{\ell}$ is determined by :

$$\rho = (\hat{\kappa}_k^{(r)} - V_{r,k}^{(\hat{\ell}-1)}) / (V_{r,k}^{(\hat{\ell})} - V_{r,k}^{(\hat{\ell}-1)}).$$

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There are the following consequences on the downstream station:

$$\forall s \in S_k\ ,\ s > r : \begin{cases} \ell_{rs}^{(\mu_{rs}(k))} = \hat{\ell} \\ \hat{y}_{rs}^{(k)} = \rho(X_{rs}^{+}(\hat{\ell}) - X_{rs}^{+}(\hat{\ell}-1)) + X_{rs}^{+}(\hat{\ell}-1) - X_{\bar{r}s}(\lambda_{rs}(k)) \\ X_{\bar{r}s}(k) = X_{\bar{r}s}(\lambda_{rs}(k)) + \hat{y}_{rs}^{(k)} \end{cases}.$$

In both case, it remains to include the resulting incoming flows $\hat{y}_{rs}^{(k)}$ in the vehicle flows for the next station $r' = s_z^{+}(r)$ along z_k:

$$\forall s \in S_k\ ,\ s > r :\ \ y_{k,s}^{(r')} = y_{k,s}^{(r)} + \hat{y}_{rs}^{(k)}\ .$$

3.4.2 The number of seated or standing passengers

In the hybrid line model, the generalized cost of travel considers whether passengers are seating or standing, following the comfort model developed by Leurent (2009). This paper derives standing and sitting probabilities for each leg (r, s). As the model is originally based on a static O-D matrix, we adapt the framework by considering the same equations, but rewriting them as a function of vehicle *k*.

The following steps assign a vehicle access–egress trip matrix to the seating and standing states along the route segments. The outputs consist in flows by state named $\underline{x}_{\geq r}^{+}$ (resp. $\overline{x}_{\geq r}^{0}$) for sitting (resp. standing) passengers. The upper index differentiates between boarding ($\delta = +$) and already aboard ($\delta = 0$) passengers, as vacant seats are given first to the latter over the former. Input variables include the access-egress trip matrix $q_{r,s}^{L}(k)$, which is derived from the outputs of the "flowing model".

Then, the line loading model algorithm addresses a route L with S_l stations and seat capacity κ.

Initialization. Let $r = 0$; let $\underline{x}_s^{(0)+}$; let $\overline{x}_s^{(0)+} = 0\ \forall s \in L$; let $\underline{x}_{>r}^{+} = 0$ and $\overline{x}_{\geq 0}^{+} = 0$.

Termination Test. If $r = S_l$, then terminate else let $r = r + 1$ and continue.

At station r:

- Let first $\kappa_r^0 = (\kappa - \underline{x}_{s\geq r-1}^{+} + \underline{x}_r^{(r-1)+})$ then $y_r^0 = \overline{x}_{\geq r-1}^{+} - \overline{x}_r^{(r-1)+}$ and $p_r^0 = \min\left\{1, \frac{\kappa_r^0}{y_r^0}\right\}$.

Standing passengers who go farther than station *r* may obtain a seat

- Let $\underline{x}_s^{(r)0} = \underline{x}_s^{(r-1)+} + p_r^0\, \overline{x}_r^{(r-1)+}$ and $\overline{x}_s^{(r)0} = (1 - p_r^0)\overline{x}_s^{(r-1)+} \forall s \geq r$.
- Let $\underline{x}_{\geq r}^{0} = \underline{x}_{\geq r-1}^{+} - \underline{x}_r^{(r-1)+} + p_r^0\, y_r^0$ and $\overline{x}_{\geq r}^{0} = (1 - p_r^0) y_r^0$.

Passengers boarding at station *s* compete for seating capacity κ_r^+

Let $\kappa_r^+ = (\kappa_r^0 - p_r^0 y_r^0)^+$, then $y_r^+ = \sum_{s>r} q_{r,s}^L$ and $p_r^+ = min\{1, \frac{\kappa_r^+}{Y_r^+}\}$.

- Let $\underline{x}_s^{(r)+} = \underline{x}_s^{(r)0} + p_r^+ q_{r,s}^L$ and $\overline{x}_s^{(r)+} = \overline{x}_s^{(r)0} + (1 - P_s^+) q_{r,s}^L \forall s \geq r$.
- Let $\underline{x}_{\geq r}^{+} = \underline{x}_{\geq r}^{0} + p_r^+ y_r^+$ and $\overline{x}_{\geq r}^{+} = \overline{x}_{\geq r}^{0} + (1 - P_r^+) y_r^+$.
- Go to Termination Test

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The number $\underline{x}^{+}_{\geq r}$ (resp. $\overline{x}^{0}_{\geq r}$) of sitting (resp. standing) passengers is used in the following steps.

3.5 Key Performance Indicators

Two sets of indicators are used to assess the performance of the TDM measures under consideration. The first set appraises the congestion relief benefits using a combination of vehicle-based and user-oriented indicators:

- number of congested links;
- total time standing (h);
- aggregate user generalized cost (€) and crowding cost (€).

It is based on the outputs of the hybrid line model presented above. The second set of indicators evaluates the rescheduling cost for users and for firms by measuring:

- the number of trips shifted;
- the mean timeshift (min), conditional to the trip being shifted.

Here it is important to stress that TDM measures only shift trips; they do not modify the overall travel demand. Consequently, TDM measures do not impact the average congestion level: the average load factor always remains the same in all scenarios and over the time period considered by construction. Rather, TDM are aimed at better spreading demand over the whole time period in order to make better use of all services and to achieve more uniform load factors, as opposed to a situation in which vehicles would be overcrowded during the peak period and mostly empty during the off-peak period. As such, the KPIs used to evaluate the efficiency of TDM measures should be sensitive to the whole distribution of load factors over services - not only to the mean - and reflect whether those are uniform or not, which is indeed the case for our first set of KPIs as we will now discuss.

3.5.1 Number of congested links

In line with Li et al. (2018), the first indicator provides the number of “links” – defined as one interstation for a given service – by load factor bracket. In the case study the following load factor brackets are used in accordance with the maximum capacity of the RER A (2,600 users/vehicle) and the total number of seats (948 seats):

- 0 to 40%: comfortable, corresponds to a situation in which all users are seated;
- 40% to 60%: moderate congestion, few users standing;
- 60% to 80%: congestion, lots of users standing;
- 80% to 100%: heavy congestion (passenger density close or equal to 4 per/m²).

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In other words, this indicator provides the distribution of load factors over services and interstations. Accordingly, the TDM is deemed successful if it manages to concentrate the distribution of load factors around its mean value.

3.5.2 Total time standing

The second indicator measures the total time that users spend standing in the transit line over the study period considered. Again, inasmuch as TDM are intended to lead to more uniform load factors, they are expected to reduce the total time spent standing as some users, by shifting their trip to less crowded periods, would become able to sit in formerly low-occupancy vehicles.

3.5.3 Generalized cost and crowding cost

The aggregate user generalized cost allows to synthesize all previous elements by considering a Value of Travel Time Savings (VTTS) that depends on the in-vehicle crowding level. For a given user *i*, her generalized cost writes as follows:

$$CG_i = VTTS_{ref} \sum_l (\alpha_0^s + \alpha_1^s K_l) T_l,$$

where $VTTS_{ref}$ is the baseline VTTS for a user seating in an empty vehicle, K_l and T_l are the load factor and the travel time for link *l*, respectively, and α_0^s and α_1^s are crowding parameters which depend on the state *s* (seating or standing) of the passenger. The generalized cost is then aggregated over all trips in order to compute the final indicator. Because the averaged VTTS (over seating and standing passengers) is a strictly convex function of the load factor, TDM measures by making load factors more uniform are expected to decrease the aggregate generalized cost (Jensen's inequality). Furthermore, the aggregate generalized cost is directly related to the consumer surplus in cost-benefit analysis.[9]

Because a large share of the generalized cost CG_i remains insensitive to TDM schemes, which only affect crowding levels (with a first-order effect on the VTTS and a second-order effect on travel times),[10] it is useful to distinguish the crowding cost CC_i by subtracting the free-flow generalized cost as follows:

---

[9] More precisely, considering that we assume inelastic travel demand (the total trip volume remains constant), the variation in consumer surplus is equal to the variation in the aggregate generalized cost plus the variation in scheduling costs (which are not included in our generalized cost as they are difficult to monetize and estimate, being proxied by the total timeshift instead).

[10] In our case study, while the level of crowding is substantial, instances of denied boarding due to the vehicle being full remain rare, so that the TDM schemes have a negligible influence on waiting times. Similary, TDM do have an impact on travel times through changes in boarding and alighting times, yet the effects remain limited in proportion of the total travel time, and thus secondary compared to the effect of crowding on the VTTS. In case of more extreme congestion as in Beijing, where denied boarding is very frequent during the morning peak (Xu et al., 2019), the effect on waiting times and thus travel times would be much more substantial.

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$$CC_i = CG_i - VTTS_{ref}\alpha_0^{seating}T_i^0 = VTTS_{ref}\left(\sum_l(\alpha_0^s + \alpha_1^s K_l)T_l - \sum_l T_l^0\right),$$

where T_i^0 is the free-flow travel time for user *i* (the hypothetical travel time were there no other users), T_l^0 the free-flow travel time for link *l*, and $\alpha_0^{seating} = 1$ (seating is the reference state).

The parameter values used in our case study are reported in **Erreur ! Source du renvoi introuvable.**. These are taken from the official guidelines for the economic evaluation of transportation projects in France (Commissariat Général à la Stratégie et à la Prospective, 2013). Regarding the VTTS, the value corresponds to the VTTS of commuting trips (to school and work) for the Paris region, based on the observation that in 2010, those accounted for 80% of public transit trips in the morning (between 6 am and 11 am).[11]

Table 1 : Parameter values for the computation of the user generalized cost in the case study

Parameter	Value
$VTTS_{ref}$	12.6 €/h
$\alpha_0^{seating}$	1.00
$\alpha_1^{seating}$	0.08
$\alpha_0^{standing}$	1.25
$\alpha_1^{standing}$	0.09

Note: here the coefficients $\alpha_1^{seating}$ and $\alpha_1^{standing}$ apply to the standing passenger density (pax/m²), not to the load factor.

Source: Commissariat Général à la Stratégie et à la Prospective (2013)

3.5.4 Number of trips shifted and total timeshift

In order to appraise its cost, we measure for a given TDM scenario the number of trips that are shifted, and the average timeshift. Following Henderson (1981), these two elements allow to capture the rescheduling cost borne by users (effect on home schedule) and by firms (effect on work productivity) consecutive to the implementation of the TDM.

Unfortunately to the best of our knowledge no valuation is currently available for long term shifts in work (or lecture) start times, precluding the conversion of the rescheduling cost from hours to euros. One might expect this long term rescheduling shadow price to be (substantially) lower than the short term schedule delay late shadow price, which is typically around 3 times the VTTS (Bates et al., 2001). This is corroborated by the empirical study of Peer et al. (2015), who find that while the short run value

[11] Source : Enquête Globale Transport 2010.

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of schedule delay late is around 4 times the VTTS, close to the typical ratio of 3, the long run value of schedule delay late only amounts to 25% of the long run VTTS. Their study focuses on road commuters, and does not consider the cost for firms of long term rescheduling decisions, however.

4 Case study: the RER A mass transit line in the Paris region

4.1 Overview of public transit supply and demand in the Paris region

Nearly 3.8 million people in Ile-de-France subscribe to a public transportation pass, adding up to more than a third (36%) of Ile-de-France inhabitants aged 6 and over (Omnil, 2015). Over the last ten years, public transit use has increased by 13% (Omnil, 2019). While expecting the future Grand Paris Express, a suburban and automatic metro network that will be progressively put in service from 2021 to 2030,[12] the public transportation network is currently mainly structured around the Regional Express Network (*Réseau Express Régional* or RER in French). The RER is a radial commuter train network that connects the capital city of Paris with its suburban areas, some of which being almost 100 km distant from the core of the metropolitan area (**Erreur ! Source du renvoi introuvable.**).

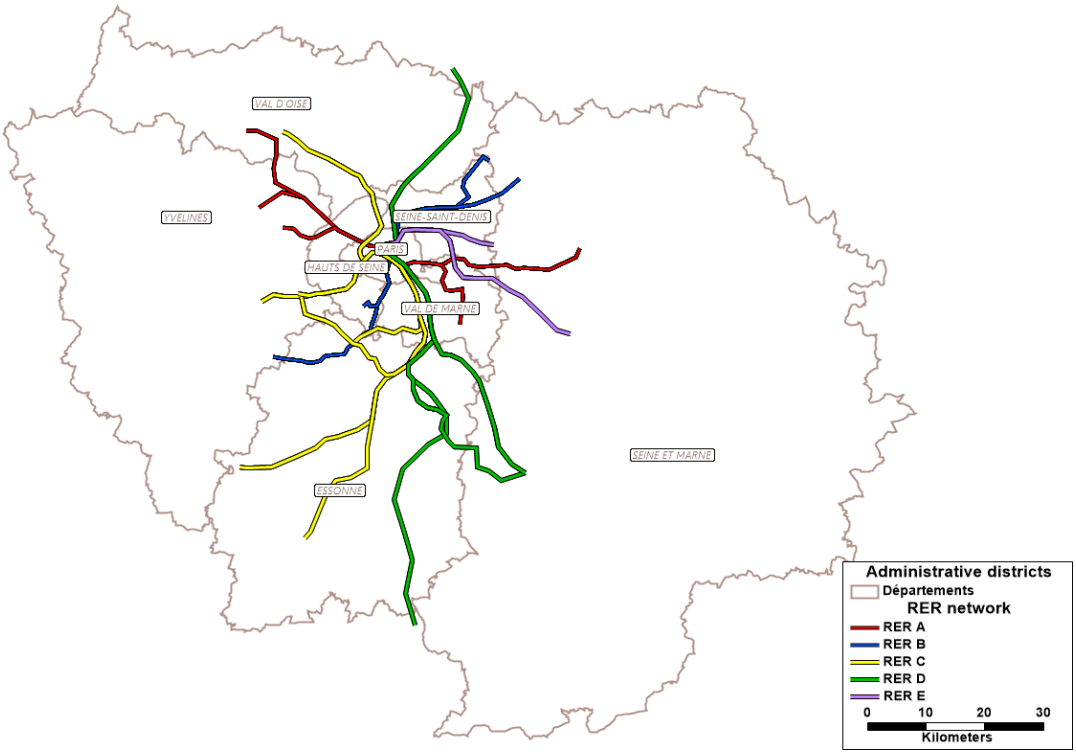

Figure 4 : The Réseau Express Régional (RER), a radial, suburban train network

The spatial mismatch between the job centers predominantly localized in the center and in the western part of the region on the one hand, and the housing stock mainly located in the east on the

[12] Source : https://www.societedugrandparis.fr/

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other hand, gives rise to significant east-west commuting flows during the morning rush hour (and conversely in the evening). This specificity of the Paris region, combined with the fact that the RER A is currently the only suburban line entirely crossing the capital from east to west (**Erreur ! Source du renvoi introuvable.**), results in the RER A being the most used urban transportation line in Europe, with more than 1.2 million passengers per day.[13] The RER A is therefore a particularly relevant case study for observing public transit congestion during the peak period and for testing the effects of travel demand management policies on decreasing congestion (i.e. crowding) and improving comfort.

4.2 The RER A line: key facts and figures

The RER A line spans approximately 100 km from the western terminus of Saint Germain-en-Laye, Cergy-Le Haut or Poissy to the eastern terminus of Boissy-Saint-Léger or Marne-la-Vallée Chessy. Its five branches serve a total of 46 stations, including several major stations in Paris (the hub of Châtelet, the intercity train station Gare de Lyon, or Charles-de-Gaulle Etoile at the top of the Champs-Elysées), the job centers of La Défense and Auber, and to the east a key touristic spot, Eurodisney (**Erreur ! Source du renvoi introuvable.**).

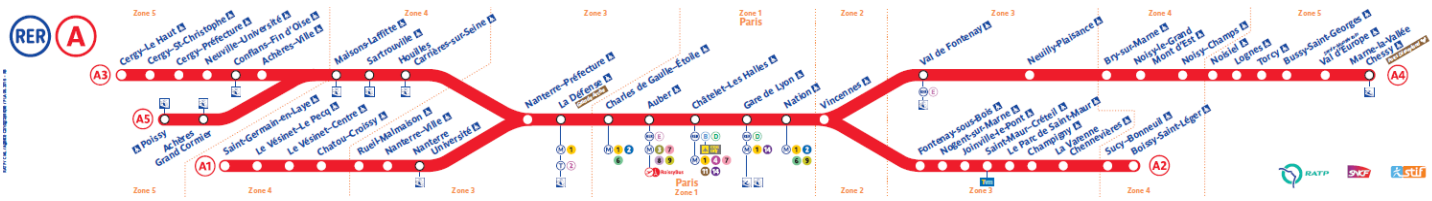

Figure 5 : Map of the RER A stations from west to east (left to right) (source: RATP, 2019)

The RER A is designed to provide very high carrying capacity during the rush hour. The line is now fully equipped with double-decker trains, for an onboard capacity of 2,600 passengers including 948 seats.[14] The line also features a recent signaling system, affording a maximum frequency of 27 trains/h during the peak period (7.30 am to 9.30 am). As a result, the maximum capacity nears 70,000 pass/h/direction, which would be roughly the equivalent of 20 highway lanes in each direction.[15] Despite the substantial capacity that it provides, the RER A line is still subject to heavy congestion during the peak periods. Crowding is especially salient in its central section (between Vincennes and La Défense) with more than 50,000 pass/h/direction on average. While this implies an average load factor of "only" 70%, asymmetries in traffic direction combined to fluctuations in demand may lead to very high load factors in some vehicles, users having to wait to board vehicles, and to recurrent delays. Indeed, the slightest initial delay, e.g. caused by an incident in operations, typically leads to a snowball

[13] Source: https://www.ratp.fr/travaux-ete-rer/les-chiffres-cles-du-rer

[14] This maximum capacity is computed based on the national standard of 4 passengers/m² at maximum.

[15] This is assuming solo drivers: the figure would be closer to 5 to 6 lanes in the case of 4 passengers per car.

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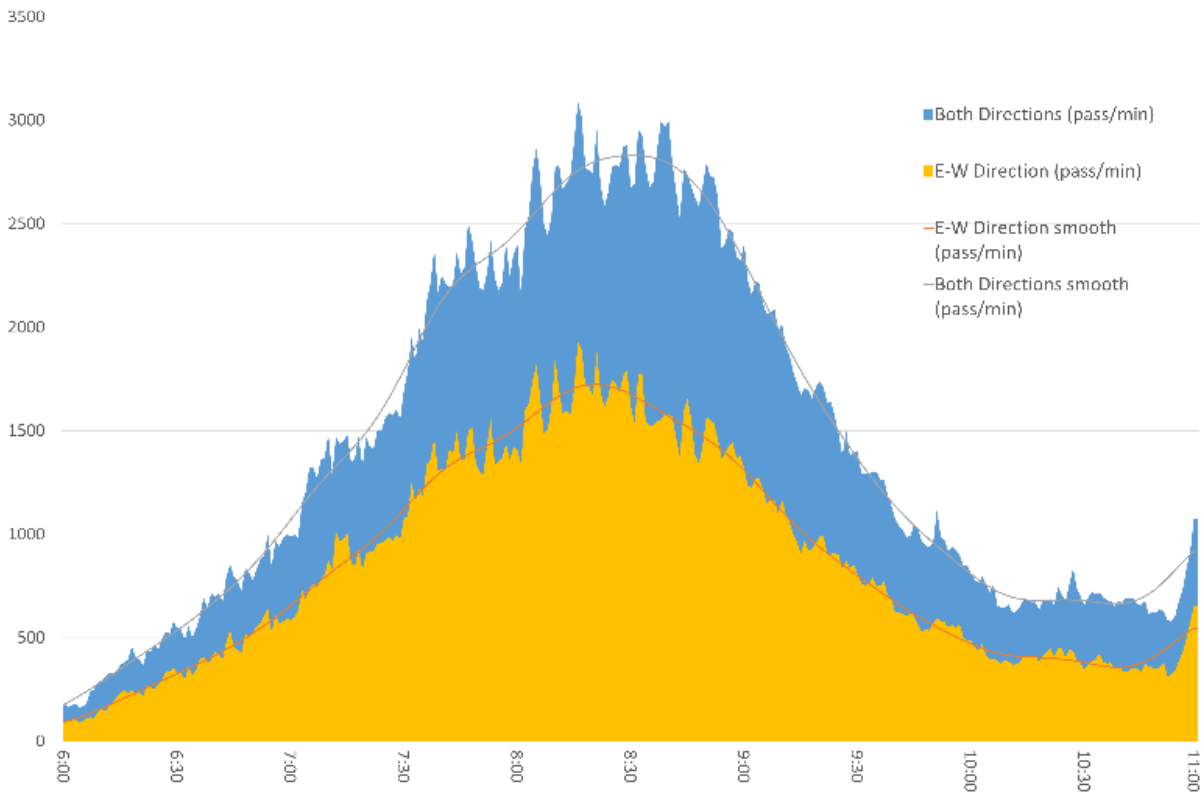
effect (through delay propagation) as dwelling times spike due to too many users on the platform seeking to board the train. Consequently, several plans have been considered to relieve congestion on the RER A. This includes the extension of the RER E between Saint-Lazare and La Défense, which is planned for the end of 2022, and more recently an experiment of staggered work hours in La Défense CBD (presented further).

4.3 Preliminary analysis of demand during the morning peak

In order to design the TDM scenarios, we carry out a preliminary analysis of travel demand on the RER A transit line. The analysis focuses on the morning peak period as most staggered work hours schemes, including the ongoing experiment at La Défense, mostly target morning trips to work rather than evening trips back home (see subsection 2.2).The analysis of travel demand confirms the strong spatial imbalance of passenger flows in the morning: westbound trips represent approximately 60% of all trips made between 6 am and 11 am (**Erreur ! Source du renvoi introuvable.**). Westbound passenger flows are therefore nearly 50% larger than eastbound ones. Considering that service frequency is the same in both directions, congestion firstly concerns westbound services during the morning peak period. Accordingly, the analysis will focus on the morning period (6 am to 11 am) and on the westbound direction henceforward.



Source : 2015 TJRF count data

Figure 6 : Time distribution of boardingsin RER A stations on an average weekday morning

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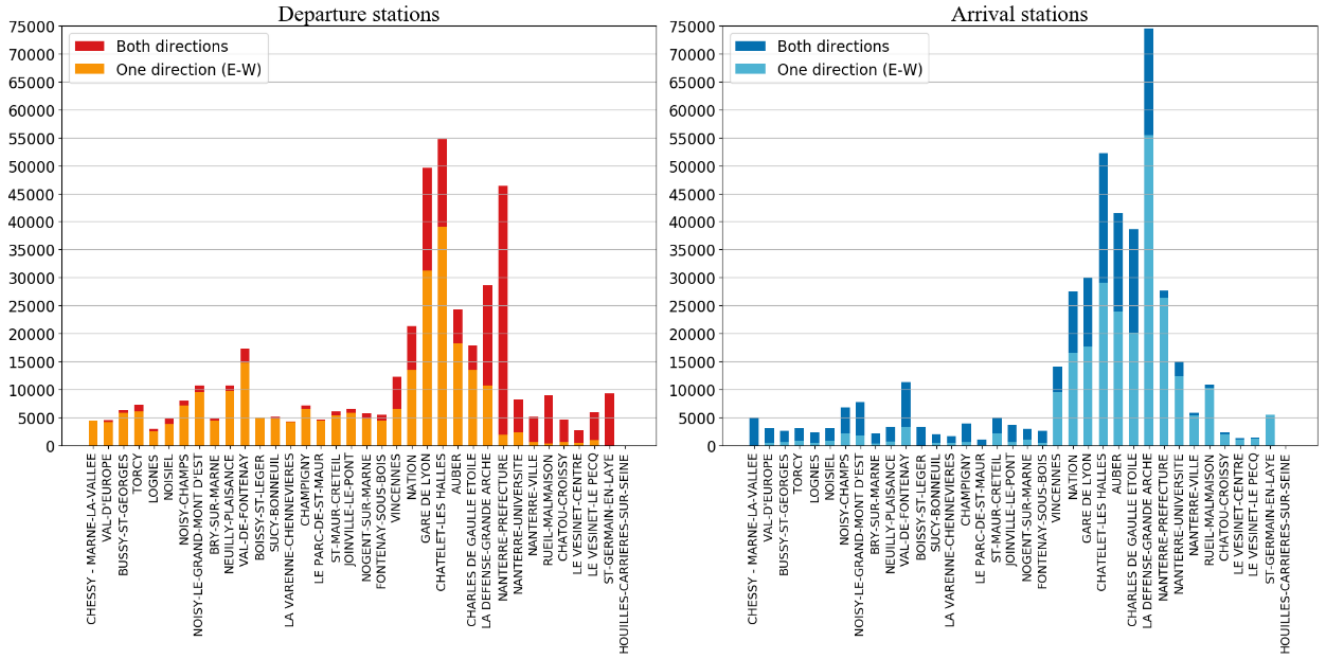

Source : 2015 TJRF count data

Figure 7 : Distribution of origins and destinations on an average weekday morning

The analysis of origins and destinations shows that the top three boarding stations in the morning – Châtelet-Les Halles, Gare de Lyon, Nanterre Préfecture – are all transfer hubs (**Erreur ! Source du renvoi introuvable.**), confirming the central role of the RER A as a trunk line in the Paris transit network. Conversely, a sizable share of trips is headed to Europe's largest central business district, La Défense, located in the west of Paris. The CBD of La Défense gathers 160,000 workers distributed across 400 companies and 71 skyscrapers. Regional planners and local authorities have strived to endow it with the best possible accessibility by public transit, so that in 2014 87% of the workers of La Défense commuted by this mode (Epadesa, 2014). This results in the station La Défense being the greatest trip generator for the RER A, attracting 22% of the whole westbound traffic, far ahead the transfer hub of Châtelet-Les Halles and the job center of Auber in Paris.

To design meaningful TDM scenarios, an analysis of the distribution of trip arrival times is also in order. As expected, the time profile of alightings depends on the station type (**Erreur ! Source du renvoi introuvable.**). While the bulk of users arrive between 8.30 am and 9.30 am if the station serves a job center (La Défense, Auber, Charles de Gaulle-Etoile), the rush hour occurs sooner, between 8 am and 9 am, in the case of transfer hubs (Châtelet-Les Halles), as users have yet to use another line to get to their final destination. These results are in line with the regional household travel survey (Enquête Globale Transport 2010) which shows that the peak-hour of arrival at work with public transit is concentrated between 8.30 am and 9.30 am (Munch, 2019).

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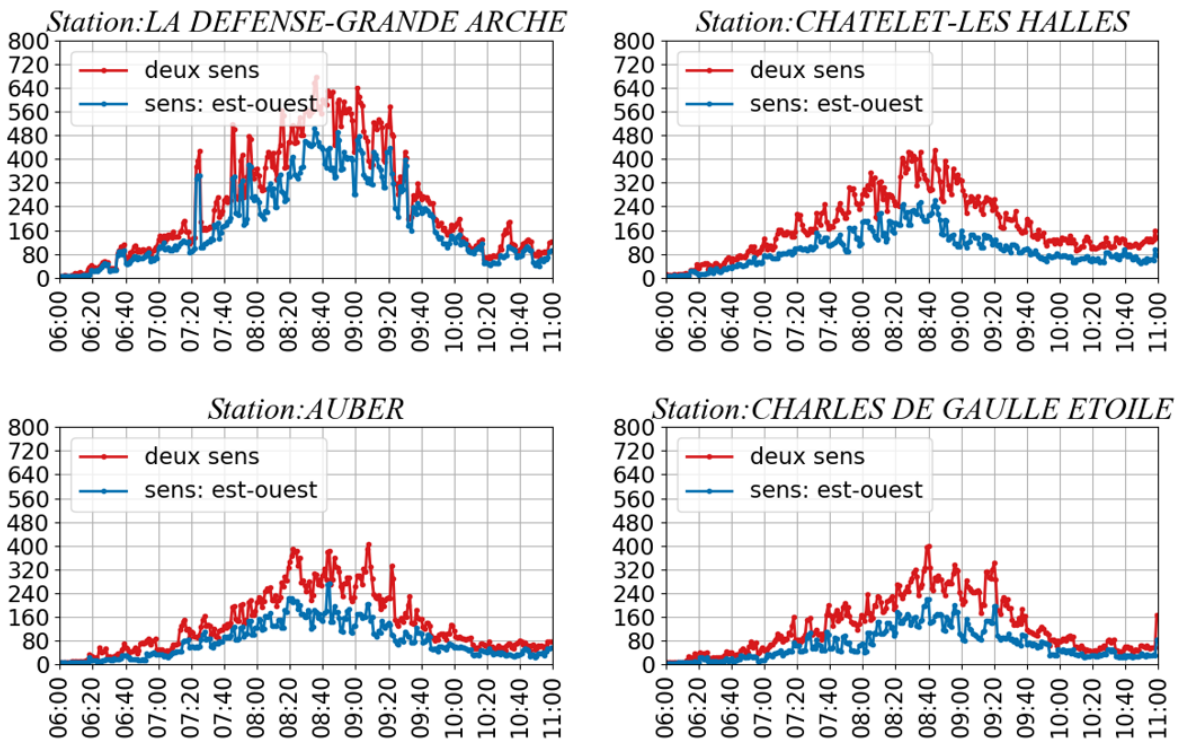

Source : 2015 TJRF count data

Figure 8 : Time distribution of alightings (in users/min) on an average weekday morning

4.4 Scenarios

Based on the preliminary analysis of travel demand, we consider two types of scenarios for the RER A transit line.

4.4.1 Centralized scenarios

The first category of scenarios corresponds to centralized scenarios in which the maximum departure rate is capped at a given threshold: trips are then shifted in order to minimize the total timeshift while satisfying this maximum departure rate constraint (see subsection 3.3.1).

Considering that in the reference scenario the observed departure rate nears 1,700 users/min at its maximum (after smoothing, see **Erreur ! Source du renvoi introuvable.**), in the centralized scenarios the upper threshold is made to vary from 1,660 users/min (very mild constraint) down to 1,220 users/min (very strong constraint).

4.4.2 Decentralized scenarios

Next, the decentralized scenarios intend to represent more realistic (or at least easier to implement) TDM policies. We focus the analysis on the two most frequent types of policies that are implemented: 1) staggered work/school hours (SWH); and 2) telework. The latter allow to contrast SWH schemes to a situation in which the trips would not be just shifted but instead cancelled. Two alternatives are

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considered for SWH schemes: trips are either shifted 50% before the rush hour period and 50% after (called "delay and advance" strategy), or all trips are delayed after the peak ("delay only" strategy). The second alternative stems from the observation that there might be more remaining seating capacity after the peak hour than before the peak hour (**Erreur ! Source du renvoi introuvable.**).

The scenarios are applied to the whole RER A transit line. In the case of SWH scheme, we also consider the case where the policy is targeted at a given station, namely La Défense. Considering the recurring crowding and congestion issues on the RER A, the CBD of La Défense has recently engaged in a TDM experiment in order to try and alleviate congestion during the morning peak-hour. The experiment began in November 2018 under the impetus of the regional authority, with the support of the two main regional public transport operators and the collaboration of 14 volunteer firms, bringing together 40,000 employees. The objective is to decrease the number of employees arriving at La Défense at the most critical time, i.e. between 8:30 and 9:30 a.m, by 10%. To achieve this goal, the participating firms have signed a "collective charter" where they commit to develop various TDM policies such as telework, alternative working schedules, or bike promotion. Because this experiment has remained at a relatively small scale for now, this work here seeks to provide an evaluation of what could be the results of such a policy at a much greater scale.

Erreur ! Source du renvoi introuvable. reviews the various TDM scenarios under consideration. In the case of the SWH schemes, trips are shifted with a (variable) probability p if the arrival time is between 8.30 am and 9.30 am, chosen as the busiest arrival period for CBD-type stations (**Erreur ! Source du renvoi introuvable.**). Because more trips are delayed in the "delay only" strategy, trips are delayed 15 minutes later than in the "delay and avance" strategy to leverage the greater remaining capacity between 9.45 am and 10.45 am than between 9.30 am and 10.30 am.

Table 2 : TDM decentralized scenarios for the RER A

Scope	Scenario	Probability of trip being : -shifted (SWH) -cancelled (telework)	Targeted trips (arrival time)	New time period for advanced trips	New time period for delayed trips
Whole line	SWH delay & advance	5 %, 7.5 %, 10 %, 20%, 30 %, 50 %	[8.30 am, 9.30 am]	[7.30 am, 8.30 am]	[9.30 am, 10.30 am]
Whole line	SWH delay only	5 %, 7.5 %, 10 %, 20%, 30 %, 50 %	[8.30 am, 9.30 am]	-	[9.45 am, 10.45 am]
Whole line	SWH delay & advance	5 %, 7.5 %, 10 %, 20%, 30 %, 50 %	[8.30 am, 9.30 am]	[7.30 am, 8.30 am]	[9.30 am, 10.30 am]
La Défense	SWH delay only	5 %, 7.5 %, 10 %, 20%, 30 %, 50 %	[8.30 am, 9.30 am]	-	[9.45 am, 10.45 am]
Whole line	Telework	5 %, 10 %, 20%, 30 %, 50 %	All morning trips: [6 am, 11 am]	-	-

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5 Results

5.1 Centralized scenarios

We first consider the centralized scenarios in which the departure rate is capped at a given level. As this threshold is set lower and lower, more and more trips are shifted before and after the peak, thereby extending the rush hour period as illustrated by the new departure time profiles (**Erreur ! Source du renvoi introuvable.**). Because only 20% of the trips are shifted earlier from the configuration of our scenarios, the rush hour period mostly extends toward the end of the morning, from 8.45 am up to 9.45 am as the threshold is set lower and lower and the TDM policy impacts more and more trips.

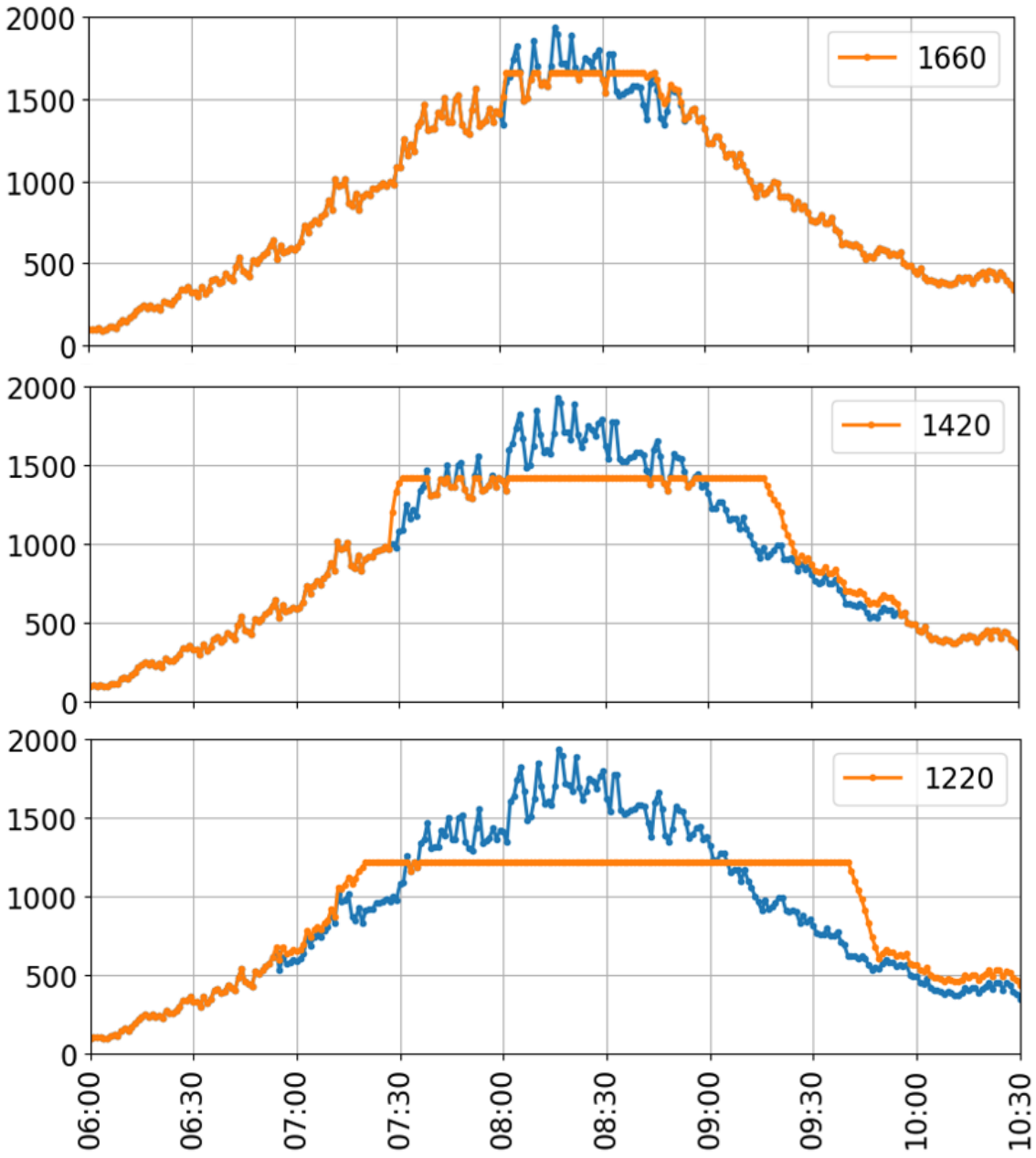

Figure 9 : Influence of the maximum departure rate on the departure time profiles (in users/min)

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By feeding the new departure time profiles to the hybrid line model, we find that as the maximum departure rate decreases, the congestion indicators also do decrease overall, as expected (**Erreur ! Source du renvoi introuvable.**). Capping the departure rate results in users being better distributed across vehicles, thus in fewer instances of severe congestion: while there are 33 heavily congested links in the reference scenario (meaning that the load factor exceeds 80% for 33 vehicle.interstations), this figure falls to 10 when the maximum departure rate is set at 1,260 users/min. Similarly, the total time standing and the aggregate generalized cost both decrease as more and more users are shifted. The indicators do not decrease strictly monotonously, however, especially at the beginning when the constraint is not very stringent. The aggregate generalized cost is for instance greater for a maximum departure rate of 1,660 users/min than for the reference scenario. Similarly, the number of heavily congested links decreases, then increases, then decreases again as the maximum departure rate gets lower and lower. These non-trivial effects are related to the fact that the centralized scenarios spread demand over the whole line uniformly, without considering possible local spikes in demand (both in time and in space) and complex network effects. Shifting trips may therefore in some (rare) cases deteriorate the situation instead of improving it.

Table 3 : Effect of the maximum departure rate on the KPI

Maximum departure rate	[0%-40%]	[40%-60%]	[60%-80%]	[80%-100%]	Total time standing (h)	Total generalized cost	Total crowding cost
Ref	*2387*	*298*	*82*	*33*	*12 148*	*853 001 €*	*90 953 €*
1660	2388	297	84	31	12 164	853 484 €	91 436 €
1620	2390	294	84	32	12 125	852 844 €	90 796 €
1580	2394	293	80	33	12 037	852 191 €	90 142 €
1540	2397	293	77	33	11 949	851 537 €	89 489 €
1500	2398	293	78	31	11 816	850 048 €	87 999 €
1460	2402	293	75	30	11 620	847 532 €	85 484 €
1420	2404	290	82	24	11 412	844 875 €	82 827 €
1380	2405	291	84	19	11 189	841 082 €	79 033 €
1340	2409	289	82	17	10 988	836 732 €	74 683 €
1300	2409	287	84	17	10 686	829 250 €	67 202 €
1260	2416	291	80	10	10 294	819 149 €	57 100 €
1220	2427	277	86	9	9 985	810 538 €	48 490 €

To give a sense of the magnitude of the congestion relief benefits to be expected from TDM policies, we isolate the total crowding cost from within the total generalized cost, obtained by subtracting the "free-flow" total generalized cost (with no crowding penalty in the VTTS) which adds up to 762,048€. We find that crowding costs amount to 10.7% of the aggregate generalized cost in the reference

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scenario. As crowding costs decreases by 46.7% if the departure rate is capped at 1,220 users/min, this means that the most ambitious scenario manages to almost halve crowding costs.

The decrease in congestion comes at the cost of an increasingly important shift, both regarding the volume of trips involved or the total timeshift (**Erreur ! Source du renvoi introuvable.**). As the maximum departure rate is set lower and lower the mean timeshift increases, though again not monotonously. This is this time related to the fact that the departure time profile for the reference scenario is not smooth but quite irregular instead (**Erreur ! Source du renvoi introuvable.**), meaning that as the threshold is set lower and lower, the locus of the users who are to be shifted may vary quite rapidly.

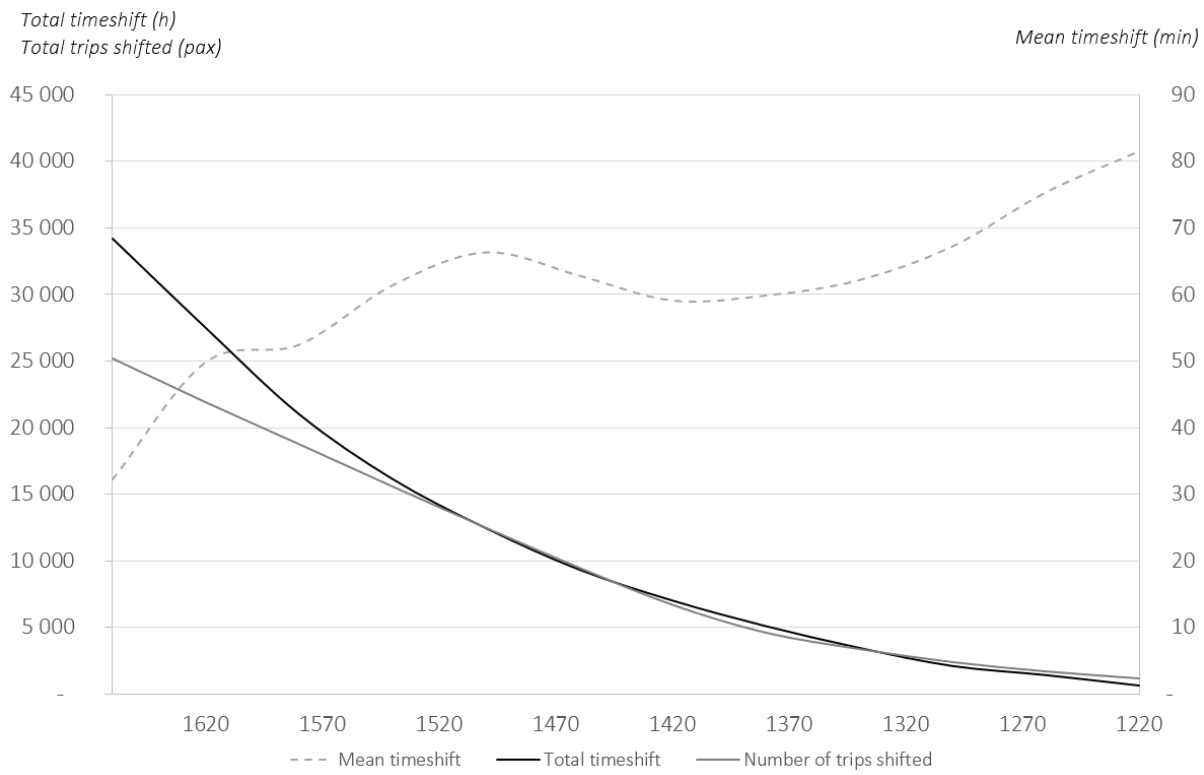

Figure 10 : Relationship between the maximum departure rate and the magnitude of the shift

In order to evaluate the performance of the various scenarios, we compare the benefits in terms of congestion relief (measured by the generalized cost savings) with the rescheduling costs for users who must change their departure time (using the total timeshift as a proxy). Generalized cost savings increase with the total timeshift (except at the beginning), as expected (**Erreur ! Source du renvoi introuvable.**). They do so first convexly then concavely (after approximately 25,000 h shifted), implying that the policy is more and more effective in relieving congestion at first, then less and less so as congestion becomes less severe. The inflexion point therefore provides a first indication of the optimal level of effort.

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This being said, the benefits to be expected remain relatively low compared to rescheduling costs. By considering a maximum departure rate of 1,260 users per hour (which is close to the inflexion point, with a total time shifted of 27,000 h), the implicit value of rescheduling that would equate rescheduling costs with congestion relief benefits would be around 1.2€/h, which is one tenth of the VTTS value. This seems unrealistically low, considering that Peer et al. (2015) find the long run value of schedule delay late to be approximately 25% of the VTTS. By looking at another metric, the total time standing, we find similar order of magnitudes: decreasing the total time standing by one hour involves shifting trips by 15 "trip.hours" (as in shifting 15 trips by one hour or 30 trips by half an hour).

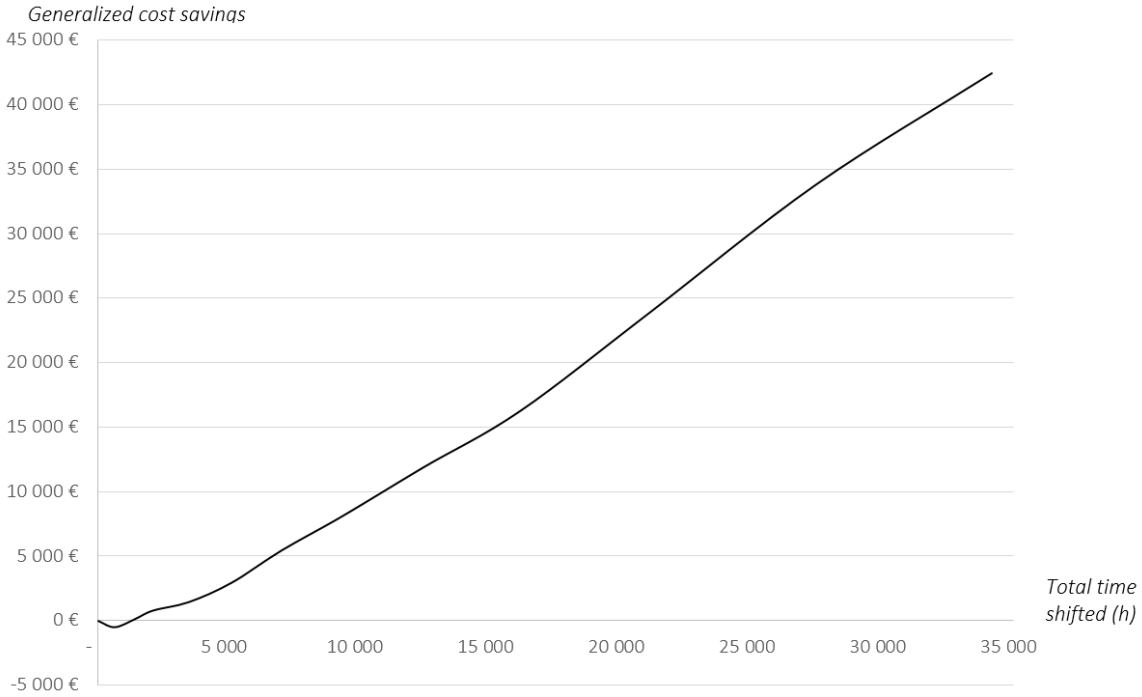

Figure 11 : Congestion relief benefits (GC savings) versus rescheduling costs (total timeshift)

5.2 Decentralized scenarios

We now turn to more realistic scenarios in which trips are not shifted according to a central planner, but based on simpler rules at the individual level.

5.2.1 Staggered work hours - whole line

We starting by consider TDM measures targeting users based on their arrival time only: trips for which the arrival time falls within the selected time interval (here 8.30 am to 9.30 am) are shifted with a given probability that varies with the magnitude of the TDM policy (see subsection 4.4.2).

As the ratio of displaced trips increases, we find again that congestion decreases at first, as expected (**Erreur ! Source du renvoi introuvable.**). For a similar share of shifted trips, spreading trips before and after the peak proves more efficient in reducing severe congestion (number of vehicle.interstations

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with a load factor above 80%), while the strategy of delaying all trips provides better results regarding the total time standing and the aggregate crowding cost. Yet, as more and more trips are shifted, the TDM measure eventually proves counterproductive as congestion rises again. Rather than spreading demand, the TDM policy then merely shifts the peak to another time period. This phenomenon arises more quickly when all trips are delayed than when trips are spread before and after the peak, in accordance with intuition.

Table 4 : Effect of the percentage of trips shifted on the KPI

Share of displaced trips	[0%-40%]	[40%-60%]	[60%-80%]	[80%-100%]	Total time standing (h)	Total crowding cost	# of trips shifted	Average timeshift
Ref	*2387*	*298*	*82*	*33*	*12 148*	*90 953 €*	-	-
Delay & advance								
5%	2393	304	78	25	11 771	85 405 €	4 511	58
7.5%	2391	311	74	24	11 603	82 930 €	6 767	58
10%	2389	313	77	21	11 454	80 683 €	9 023	58
20%	2388	313	83	16	11 076	74 020 €	18 047	58
30%	2379	325	83	13	11 018	70 901 €	27 070	58
50%	2393	278	109	20	11 906	75 542 €	45 118	58
Delay only								
5%	2392	306	77	25	11 583	82 094 €	4 511	83
7.5%	2393	311	70	26	11 346	78 215 €	6 767	83
10%	2389	319	69	23	11 138	74 706 €	9 023	83
20%	2390	314	71	25	11 315	76 906 €	18 047	83
30%	2410	296	62	32	11 527	80 246 €	27 070	83
50%	2449	232	64	55	12 574	103 822 €	45 118	83

We now compare the relative efficiency of the various measures by plotting the generalized cost savings against the total timeshift (**Erreur ! Source du renvoi introuvable.**). This corroborates that for the decentralized scenarios, only delaying trips proves more efficient at first in reducing the total crowding cost than spreading trips before and after the peak. This counterintuitive result is related to the fact that the departure time profile is not symmetric, but rather positively skewed (see **Erreur ! Source du renvoi introuvable.**). In other words, departures are more concentrated before the peak, and more spread after the peak, so that it is more efficient to delay the trips than to advance them as there is more remaining capacity after the peak. When a sizable amount of trips has already been displaced, the “delay only” strategy becomes less efficient than the “delay & advance” strategy, however. As the remaining capacity after the peak has been exhausted, delaying trips any further proves ineffective, while the “delay & advance” strategy still manages to make use of the remaining capacity before the peak.

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More surprisingly, provided that the total timeshift remains below a certain threshold, we also find that the decentralized scenarios prove more efficient than the centralized ones to relieve congestion. This seems to indicate that given that the rush hour spans over a very long time period on the RER A, it is more efficient to shift fewer trips but by a longer time interval (as in the decentralized scenarios), than to shift more trips but by a much shorter amount of time (as in the centralized scenarios). Notwithstanding, as the total timeshift increases more and more, congestion keeps on decreasing in the centralized scenarios, whereas generalized cost savings plateau for the decentralized scenarios, eventually turning into losses. This corroborates that ultimately the centralized scenarios are better designed to decrease congestion uniformly, while the simpler rules of the decentralized scenarios show their limitations when put to the extreme.

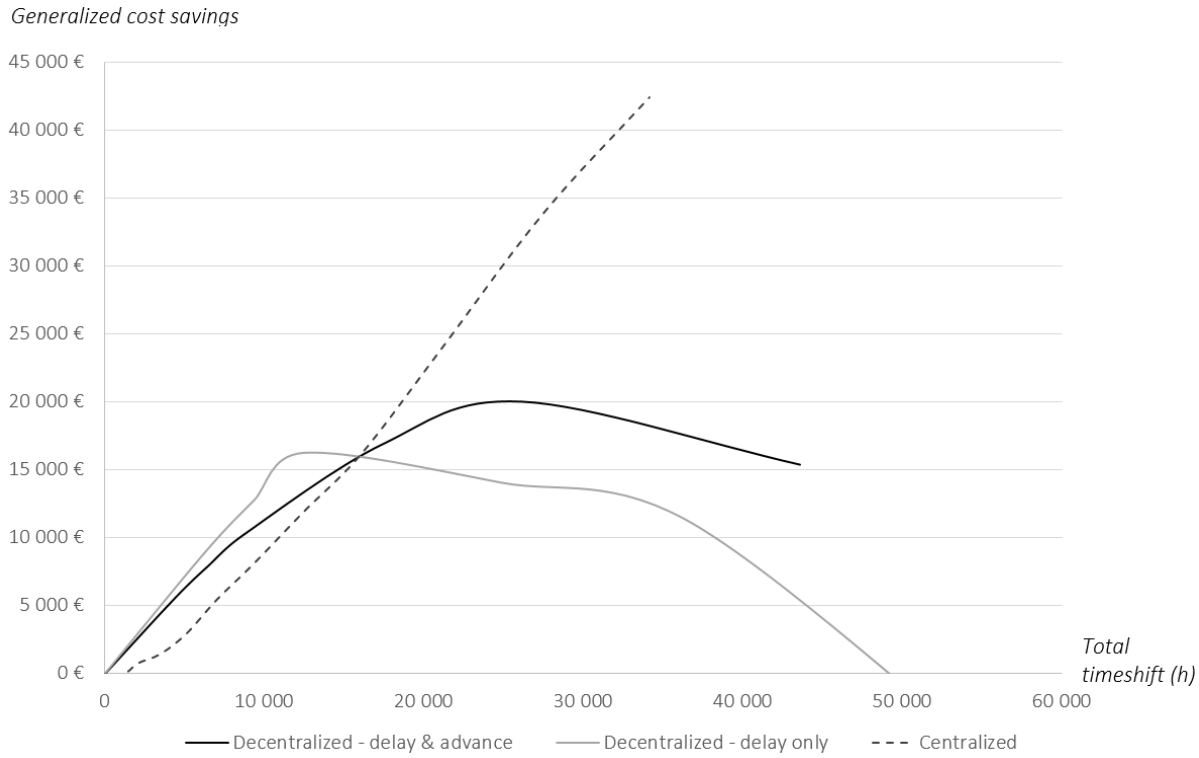

Figure 12 : Congestion relief benefits (GC savings) versus rescheduling costs (total timeshift)

5.2.2 Staggered work hours - La Défense

We consider the case where the TDM measure is targeted at a specific exit station: La Défense. While the overall patterns remain the same as previously, for a similar share of trips displaced (in %) the number of trips impacted is now considerably smaller, so that the congestion relief effect is accordingly also weaker (**Erreur ! Source du renvoi introuvable.**).

A key issue is whether it is more efficient to target the busiest station (here La Défense) or to target all users indiscriminately. From the comparison of the generalized cost savings with the total timeshift, we find that while focusing on La Défense seems moderately more efficient at first when the measure

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is very limited in magnitude, policies aimed at all users ultimately prove more efficient as more and more trips are shifted (the dashed lines being above the plain lines in **Erreur ! Source du renvoi introuvable.**). When considering a reasonable range for the share of arrivals shifted in La Défense (i.e. 0 – 30%), the relative efficiencies of both policies (targeted at La Défense or indiscriminate) remain very close, however. This being said, the benefits that may be expected from staggered work hours do not loom large: crowding costs decrease by 9.5% at maximum.

Table 5 : Effect of the percentage of arrivals shifted in La Défense on the KPI

Share of displaced trips	[0%-40%]	[40%-60%]	[60%-80%]	[80%-100%]	Total time standing (h)	Total crowding cost	# of trips shifted	Average timeshift
Ref	*2387*	*298*	*82*	*33*	*12 148*	*90 953 €*	-	-
Delay & advance								
5%	2389	300	82	29	12 032	89 540 €	1 142	54
7.5%	2391	299	83	27	11 978	88 878 €	1 713	54
10%	2390	299	85	26	11 928	88 254 €	2 283	54
20%	2390	308	80	22	11 761	86 111 €	4 567	54
30%	2383	315	81	21	11 622	84 385 €	6 850	54
50%	2396	299	86	19	11 482	82 346 €	11 417	54
Delay only								
5%	2391	298	82	29	11 981	88 973 €	1 142	73
7.5%	2393	297	83	27	11 902	88 046 €	1 713	73
10%	2391	299	83	27	11 825	87 158 €	2 283	73
20%	2393	305	76	26	11 554	84 069 €	4 567	73
30%	2390	309	72	29	11 519	83 278 €	6 850	73
50%	2387	308	75	30	11 650	85 345 €	11 417	73

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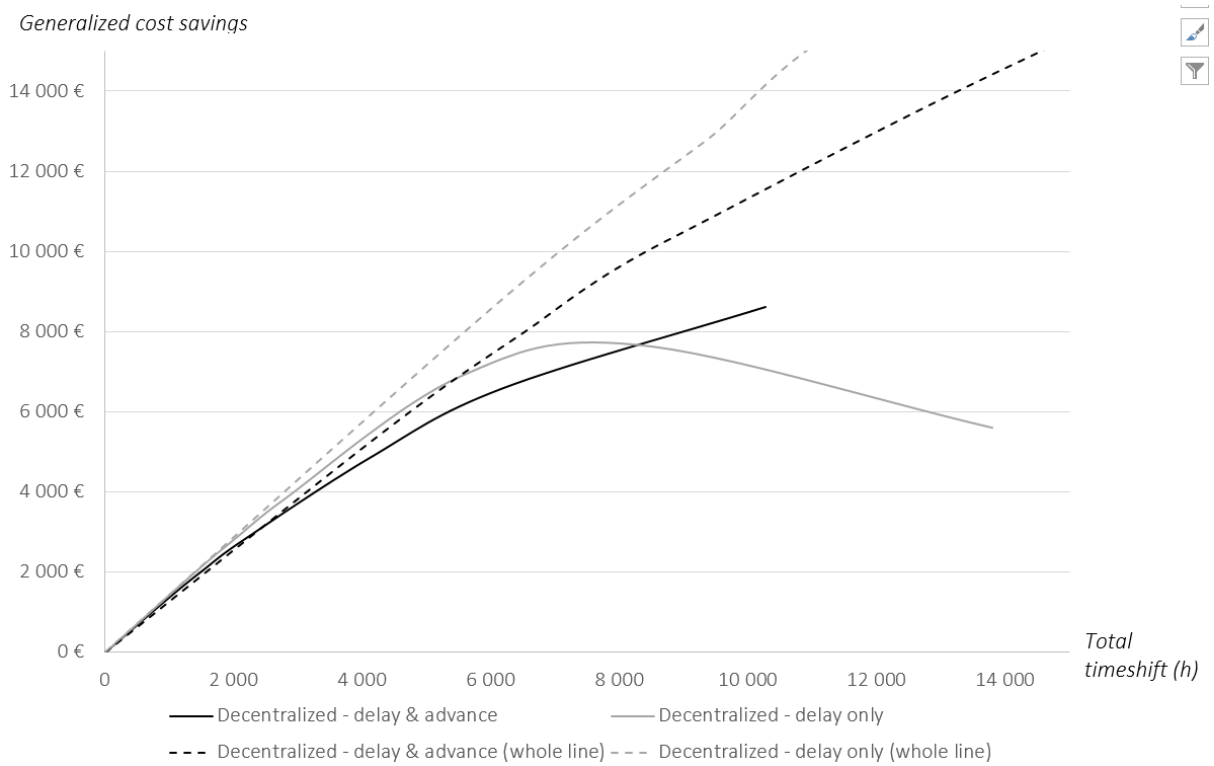

Figure 13 : Congestion relief benefits (GC savings) versus rescheduling costs (total timeshift)

5.2.3 Telework – whole line

Finally, we investigate the effects of telework scenarios in order to contrast our previous results with a situation in which the trips would not be just displaced but cancelled instead. As expected, telework has a strong mitigating impact on congestion: when the share of cancelled trips reaches 30%, heavy congestion virtually disappears (**Erreur ! Source du renvoi introuvable.**). Focusing on the unit crowding cost per trip to make things comparable, the latter decreases by around 74.4% as the share of cancelled trips reaches 50%, meaning that removing half the trips cancels out almost three quarters of the total crowding costs. The decrease of the unit crowding cost slows down as more and more trips are cancelled (**Erreur ! Source du renvoi introuvable.**), in accordance with the convexity of crowding costs.

By comparison to the SWH schemes for the whole line, we find that delaying and advancing 20% of peak trips (adding up to 8% of all morning trips approximately) has an effect similar to cancelling around 8% of all morning trips (as seen from the two curves intersecting at that point in **Erreur ! Source du renvoi introuvable.**). Shifting one peak trip (arrival between 8.30 am and 9.30 am) would therefore yield a congestion relief benefit equivalent to cancelling one morning trip (departure between 6 am to 11 am). This result stems from peak trips causing the largest crowding externality, while trips before and after the peak hour are typically associated with a very low crowding externality. While a telework policy focused on peak trips would undoubtedly yields benefits larger than a staggered work hour

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policy, this tends to show that our scenarios remain quite effective in mitigating congestion by comparison with much more drastic solutions such as telework.

Table 6 : Effect of telework on the KPI

Share of cancelled trips	[0%-40%]	[40%-60%]	[60%-80%]	[80%-100%]	Total time standing (h)	Total crowding cost	Decrease in unit CC
Ref	*2387*	*298*	*82*	*33*	*12 148*	*90 953 €*	-
Telework							
5%	2430	280	69	21	10 290	800 352 €	11.6%
10%	2479	249	59	13	8 522	749 010 €	22.8%
20%	2573	183	40	4	5 446	650 885 €	43.3%
30%	2658	125	17	0	3 089	559 139 €	59.6%
50%	2763	37	0	0	525	392 659 €	74.4%

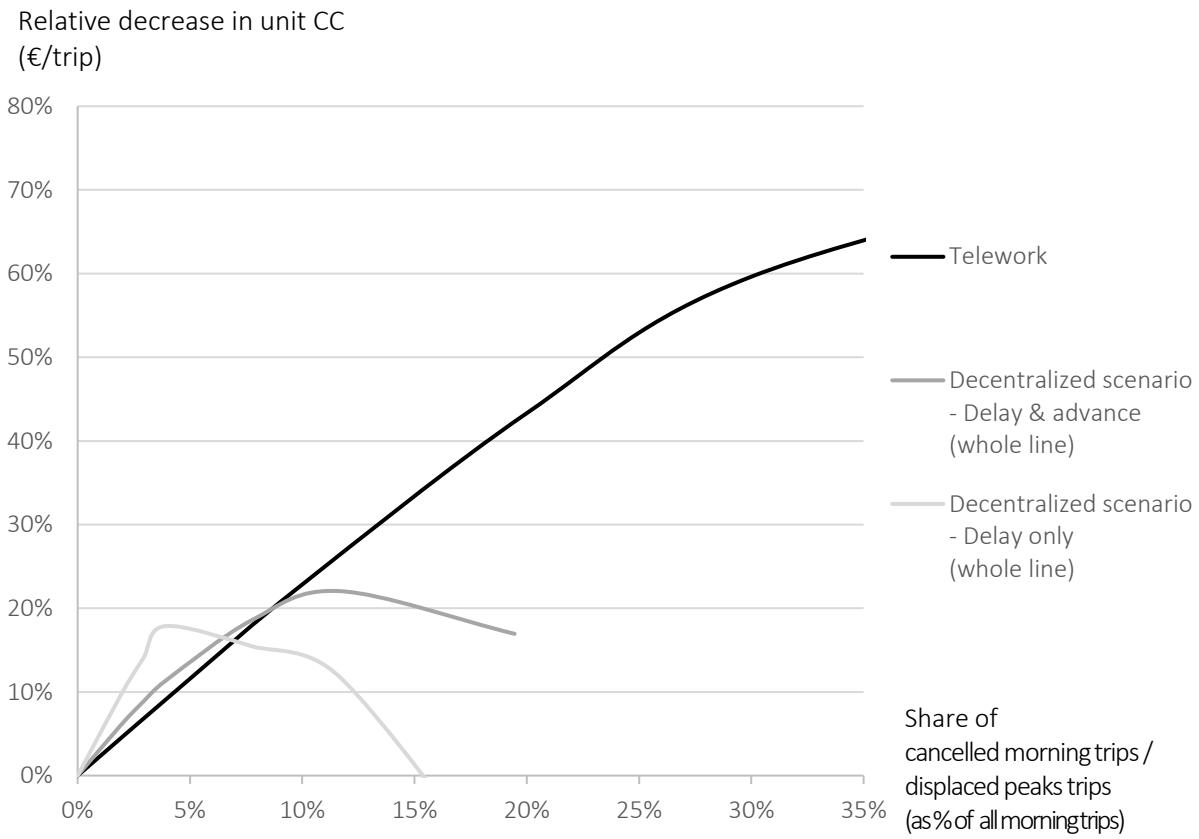

Figure 14 : Influence of the volume of cancelled morning trips/displaced peak trips (as a share of total morning trips) on the decrease in the unit crowding cost

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6 Discussion

6.1 Main results and policy implications

In order to reduce congestion on the RER A transit line, several TDM policies have been investigated. As expected, all TDM policies achieve their original purpose (within a reasonable range). They smooth the peak and better distribute users across vehicles, thereby reducing instances of heavy congestion (number of vehicle.interstations with load factor > 80%) and improving comfort for users as a whole (decrease in total crowding costs). The overall improvement in comfort does not imply that all users see their travel experience improve, however. Peak hour "stayers" who keep travelling during the rush hour benefit the most from TDM policies (by enjoying lower congestion for no rescheduling costs), while off-peak "stayers" who already travelled off-peak before the TDM policy are on the other hand worse off (as they experience greater congestion than before). This is in line with previous findings from ex-post evaluations which show non-participants to be the first beneficiaries of SWH programs (Giuliano and Golob, 1990).

For a same total timeshift (number of users shifted x the amplitude of the shift), we find that it is usually more efficient to shift few users by a large amount of time (as in the decentralized scenarios), than to shift many more users yet by a shorter amount of time (as in the centralized scenarios). However, if one seeks to enforce the policies at a much greater scale, decentralized policies tend to yield counterproductive results as they just transfer the peak at some other time in the morning. Centralized policies on the other hand by better coordinating users keep improving comfort (overall) as they are scaled up. Similarly, the choice of whether one should encourage users to advance or delay their trip should be supported by a preliminary diagnosis of travel demand. In the RER A case study, we find that for TDM schemes of limited magnitude, the "delay only" strategy is more efficient than the "delay and advance" strategy by leveraging the substantial capacity margins after the peak. However, at some point it becomes more efficient to distribute trips before and after the peak hour, lest recreating heavy congestion after the peak. Policy design should therefore carefully consider what scale is envisioned and the current state of the transit system (travel demand and capacity margins) before deciding on which kind of rules and coordination level to implement.

Regarding the policy scale, in addition to the issue of the overall magnitude in terms of users shifted, another issue relates to the spatial scale. Here we find that targeting the main generator - the CBD of La Défense - yields a decongestion effect similar to deploying the measure over the whole RER A line. This result might come as disappointing at first as one might have expected even better performance when focusing on the congestion node. Nevertheless, it remains significantly easier to implement SWH

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schemes around a given station than over a whole line, be it in terms of communication, coordination… Our results therefore support the choice of local TDM measures (up to a certain scale).

This being said, we find contrasted results regarding the efficiency of TDM policies in the case of the RER A. On the one hand, we find that decentralized SWH schemes are very efficient at a small scale. They perform better than the centralized scheme tested here, and even yield an effect comparable to telework (in that one shifted peak trip is equivalent to one morning trip cancelled by telework). Yet, decentralized SWH schemes only manage to abate aggregate crowding costs by around 20% at most. Larger reductions of crowding costs may only be achieved through centralized procedures (or significant telework measures). These results are in line with Li et al. (2018), who find only very modest congestion relief benefits to be expected from off-peak discounting (as the maximum load factor decreases from 111% to 105%). Moreover, SWH programs involve very substantial rescheduling costs. We find that decreasing the total time standing by one hour implies shifting fifteen trips by the same amount of time. Alternatively, we find an implicit long term rescheduling cost of one tenth the VTTS, which seems unrealistically low compared to the ratio of 25% reported in Peer et al. (2015).

6.2 Limitations and future works

Our results are subject to a number of caveats. Regarding travel demand, we assume relatively simple behaviors from users. In the case of centralized scenarios, shifted users are assumed to strictly follow their assigned departure time. While we do not address here the feasibility of such schemes (which would likely be implemented using trip planner mobile apps), small deviations from the planned departure rates should not affect our main results. Indeed, centralized scenarios cap the departure rate well below the maximum instantaneous rate that the system can accommodate, so that snowball effects are extremely unlikely to occur consecutive to small disturbances in demand (or in supply). Regarding the decentralized scenarios, we assume that users adhere to simple rules: leave X minutes earlier or Y minutes later. Alternate rescheduling rules such as random departures within a given time interval have been tested and were found to yield similar results. Yet two points of attention remain. Shifted users should divide themselves before and after the peak in proportions similar to the plan, which in the case of SWH schemes may be achieved through proper coordination of the firms involved. Users might also want to stick as close as possible to their original schedule, in which case shifted trips would not be spread evenly between 7.30 am and 8.30 am, but instead form a mass around 8.30 am.

For us, this raises a salient point of the problem that is not fully addressed in the article. It demonstrates that SWH policies are based on a conceptual framework close to traffic engineering that is redeployed to form a type of work schedule engineering. In this way, SWH policies are deploying methods that can be described as social engineering (Bourdieu, 1993). This analytical framework

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denies the subjective dimension of time, its appropriation and its representations on an individual scale, is based on the reading of pawn movements on the flow chessboard. The logic behind these TDM policies is that one can build a SWH project by starting the reflection from the social optimum. One then imagines the action of a central planner acting directly and with the greatest "firmness" on the structure of the daily agendas of each individual. The organic reality of the negotiation, synchronization and coordination of the social times of daily life is quite different. Time and the choice of working hours, before being a rare commodity that can be managed, is above all a private "good" that each individual – employer or employee - is appropriated both to meet personal objectives and to fit in with social rhythms (Munch, 2020). Ideally, in order to hope to shift work schedules to spread out the concentration of travel during rush hour, it would first be necessary to ensure that plans for schedule changes are feasible but also desirable for both workers and employers.

Consequently, preliminary surveys could be used to evaluate to what extent local employees are able to shift their departure in order to detect possible issues on this side (Munch, 2017). Last but not least, we assume that other users do not change their travel behavior. Because TDM schemes reduce congestion during the peak hour, and conversely increase it during the off-peak hour, off-peak users might react to the change in travel conditions by changing their departure time for some less crowded time during the off-peak period, or even by departing during the now less crowded period. While the net impact on total crowding costs of such equilibrium mechanisms remains ambiguous, if the latter effect (off-peak users reverting back to the peak) prevails, the rebound effect could then strongly mitigate the efficiency of TDM schemes. We can here draw a parallel with ridesharing, which by decreasing road congestion was shown to yield very substantial rebound effects (Coulombel et al., 2019).

Regarding the evaluation methodology, the results are based on a reference situation that corresponds to an average weekday morning of year 2015. Yet demand varies from one day to another: analysis of smart card data show deviations from +/- 12.5% at maximum from the morning average trip volume. Given these limited fluctuations of travel demand, the reference average situation is likely to provide a reasonable estimate of the true mean effect of the policy. The latter could be assessed more precisely using Monte-Carlo simulation or by replicating the methodology for several days of smart card data were such data to be available. Next, crowding costs are estimated using reference values from the French official guidelines. These imply that the VTTS ranges from a relative value of 1 for a seating passenger in an empty vehicle, to 1.61 for a standing passenger in a fully crowded train.

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While such values are overall relatively typical from the literature (Wardman et al., 2016)), in the case of a fully crowded train the fact that the VTTS increases "only" by 61% might be questioned. This point is especially salient as it explains why TDM policies are found to have a modest effect when evaluated using CBA indicators. Greater crowding multipliers, especially in the case of very heavy congestion, would lead to much more sizable effects of TDM schemes as these do not remove congestion but do smooth the load factors. Finally, a full CBA of TDM schemes could shed better light on the economic relevance of such measures. This would involve measuring the financial costs (communication, monitoring…), and more importantly estimating the rescheduling costs for users and for firms. To the best of our knowledge the literature on this side remains limited, especially for firms. For users a first appraisal of rescheduling costs could be achieved using revealed preferences (Peer et al., 2015) or stated preferences surveys.

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