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# Modeling dwell time in a data-rich railway environment: with operations and passenger flows data

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## Abstract

We model dwell times for trains subject to a possibly dense timetable based on a rich data set containing both railway operations variables and passenger flows variables, which is rare in the literature. Another distinguishing feature of our modeling consists of building a single statistical model for actual dwell times at all stations and in all contexts, not just in constrained situations like late arrivals or not just a model for some minimum dwell time. These models are fully data-driven and stem from either linear regressions with multiplicative effects or machine-learning methods like random forests, both carefully tuned on training data sets. While railway operations variables remain key for the modeling of dwell time, we are able to characterize the added value of passenger flows variables. Overall, they lead to an average reduction of the global modeling error by about 0.5 s, with up to 5 s – 10 s average improvements in challenging situations consisting, e.g., of late arrivals or associated with high affluence. We also study which are the most influential variables among the available operations and passenger flows variables, and we do so globally and by regime of punctuality: for instance, passenger flows variables, and in particular, the affluence at the critical door, are the most influential variables for trains suffering a late arrival, while the scheduled dwell time and the deviation to the scheduled arrival time are the most important variables for early trains.

**Keywords:** Dwell time; timetables; modeling; passenger flows; machine-learning methods (linear regression, random forests, gradient boosting with trees)

## 1. Introduction and literature review

We model dwell times for trains subject to a possibly dense timetable (up to 24 trains per hour during peak hours) in the greater Paris area (SNCF operator). We do so based on two sets of variables: railway operations and timetable (scheduled dwell time, deviation to scheduled arrival time, train length, etc.), on the one hand; passenger flows (numbers of alighting and boarding passengers, occupancy rate), on the other hand. We consider two railway lines, one significantly more dense than the other, but with a common point: the vast majority of their trains is equipped with automatic passenger counting

(APC) device at each door. We may therefore use the breakdown of alighting and boarding numbers by door, with a particular interest on the critical door.

Only few earlier references could use such a combination of variables based on railway operations and on passenger flows. Among these, Cornet et al. [2019] rely on similar data (same greater Paris area, same SNCF operator) and model some excess dwell time with respect to some minimum dwell time (see below), solely based on passenger flows and not using the available railway operations variables. Also, Palmqvist et al. [2020] model dwell times in a setting with a more flexible and less precise timetable (main line trains in Sweden), relying on passenger flows (alighting, boarding, and crowding factor) and on the deviation to scheduled arrival time; their contribution has, however, cannot leverage a variable like the scheduled dwell time  $y^{\text{theo}}$ , as the latter equals a single value of 42s for all stations and trains. Thus, the quality of railway operations data prevents a direct comparison of their results to ours; in particular, they had not exhibited any effect of deviation to scheduled arrival time on dwell time, which is, on the contrary, one of the main determinants of our models for dwell time.

Our approach is to build a single statistical model for dwell times at all stations and in all contexts, which the literature does not often offer. A key variable to be considered to that end is the regime of punctuality of a train at a given station (early arrival, i.e., arrival before the theoretical arrival time; late arrival, i.e., arrival after the theoretical departure time; arrival on time, i.e., arrival between the theoretical arrival and departure times). An important note at this stage is that we directly tackle the dwell time (the difference between the departure and the arrival times), and not some notion of “minimum” dwell time (given, e.g., by the alighting and boarding time, or by restricting the attention to the dwell time in constrained situations like late arrival).

We process the variables described above using linear regressions with or without interactions, as well as standard machine-learning methods (random forests, gradient boosting with trees, neural networks), as in Kecman and Goverde [2015]. Models inspired by the latter will form our benchmark, as they tackle dwell times in all situations, including early arrivals—which most references do not offer. As in Kecman and Goverde [2015], these benchmark models will be built solely on operations variables: with our data set we will then be able to characterize the added value of passenger flows variables to model dwell time in a railway context. In particular, we want to determine when and how much passenger flows impact railway operations.

We now detail several streams of the literature alluded at in the overall view provided above.

**Dwell time modeling solely based on railway operations and timetable constraints.** On a data set of railway circulation between the Hague and Rotterdam with scheduled stop, Hansen et al. [2010] exhibited a piece-wise linear relationship between dwell time and arrival delay: trains that are early or on time experience average dwell times that decrease with the earliness factor  $\Delta a$ , while the average dwell times of trains out of schedule are independent of how late these trains are. Of course, an explanation is that train drivers must wait the theoretical departure time even if the alighting and boarding process is over. We obtain a similar relationship on our data set, see Figure 3. Kecman and Goverde [2015] also consider data collected on trains circulating between the Hague and Rotterdam: their scheduled dwell times  $y^{\text{theo}}$ , deviations  $\Delta a$  to scheduled arrival time, and train types. These variables are also available on our data set and we formally define them in Section 2. They process these variables using linear regression-type methods or random forests and note that the thus constructed models for dwell times should still be improved.

Of interest is also the literature that rather aims to forecast dwell times, e.g., in some auto-regressive manner by considering past dwell times as features (at the same station for earlier trains or at earlier stations for the same train). We may cite Pritchard et al. [2021] for a UK railway network, though they only discuss delayed trains. (See also Li et al. [2016], for a Dutch railway network without a strict theoretical departure time.)

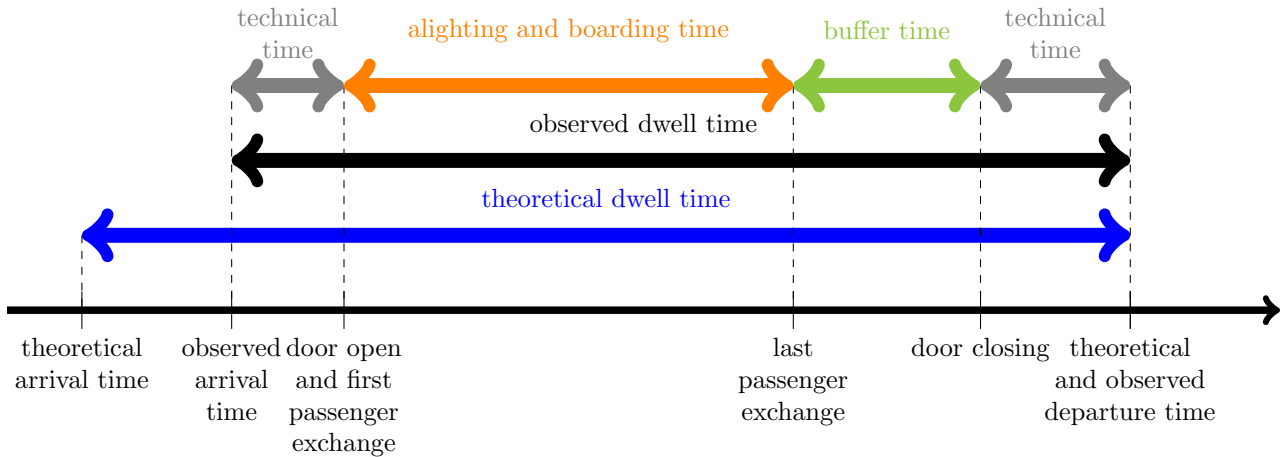


Figure 1: Decomposition of the total dwell time in railway context.

**Modeling of (lower bounds on) dwell time based on passenger flows.** The impact of passenger flows on dwell time was first and mostly studied for transportation means without a strict theoretical departure time, like bus, metro or light railway (as these passengers flows are then the only source of information to model dwell time). The seminal work of Levinson [1983] for buses exhibited an affine relationship between dwell time at the bus scale and affluence, i.e., the sum  $A + B$  of the number of alighting  $A$  and boarding passengers  $B$ . Lin and Wilson [1992] for light railway in Boston and Puong [2000] for metro also in Boston (MBTA Red line) studied a multiple linear regression modeling with variables  $A$  and  $B$  considered separately and together with a crowding factor  $C$ . All these references were based on small-scale data obtained by human observations.

For the mass transit modes described in the previous paragraph, the dwell time equals the time for alighting and boarding (also known as the exchange time—depicted in orange in Figure 1), i.e., the time between the first passenger exchange and the last passenger exchange, plus a technical time around the latter (e.g., to open and close the doors and to arrive or leave the stop—in grey in Figure 1). In a railway context with strict theoretical departure time, dwell time contains a third component: a buffer time (in green in Figure 1), corresponding to some additional waiting time (till the strict theoretical departure time) when the train is early. This buffer exists by design, as some operational margin is usually added when timetables are conceived, for the sake of robustness. The literature thus rather focused on some lower bounds on the dwell time, or on the dwell time in constrained situations like late arrivals when there is no buffer time.

Among them, Buchmüller et al. [2008] studied the alighting/boarding time only for train stops without theoretical departure time constraints. Pedersen et al. [2018] and Medeossi and Nash [2020] reduced their attention to delayed trains (for which it is essentially assumed that their dwell times equal the alighting/boarding time plus a technical time, as in the case of buses and metros). The intuition behind the descriptive study by Pedersen et al. [2018] was indeed that passenger flows variables should be useful in these situations. Finally, Cornet et al. [2019] introduces some concept of empirically minimal dwell time, which they then model (essentially in some affine way). Their concept stems from running a PCA on the dwell time based on the numbers  $A$  and  $B$  of alighting and boarding passengers and the load  $L$  of the train; it turns out that the scatterplot of dwell time on the first principal component of this PCA reveals an affine lower bound.

We will propose a complete modeling of dwell time (i.e., for all stations and all trains) using passenger flows variables on top of railway operations variables. In the presence of a strict theoretical departure time, passenger flows variables provide useful additional information for dwell time modeling on top of railway operations variables (which remain the most critical variables to be used).

**A specific discussion of passenger flows by door.** It is intuitively clear (and was later demonstrated) that alighting/boarding time discussed above depends on the affluences  $A^i + B^i$  by door  $i$  and not only on the total affluence  $A + B$ . However, these affluences  $A^i + B^i$  are not uniform at all and strongly depend, for each station, on the closeness to the entry/exit of the platform (see the studies by Wirasinghe and Szplett [1984] and Wiggenraad [2001]). Yet, most data sets with passenger flows measure them only at the train scale and not at the door scale; their treatment then has to rely on an unrealistic assumption of uniform distribution of affluence by door, i.e.,  $A^i + B^i = (A + B)/I$ , where  $I$  is the number of doors. For recent examples, see Palmqvist et al. [2020] and Medeossi and Nash [2020]. (We note that Wirasinghe and Szplett [1984] proposed a theoretical model based on Gumbel’s distribution for boarding numbers by door based on the location of exit/entry platforms and the number of doors.)

On the contrary, our data set is richer than the one of Cornet et al. [2019] as it also contains door-by-door measures  $A^i$  and  $B^i$  of alighting and boarding numbers. We may then define the critical affluence  $M$ , which is the maximum of the  $A^i + B^i$  over the doors  $i$ , and see its added value on the modeling. If there is some, then, somehow, it is proven that the assumption of uniform distribution of affluence by door is unrealistic. We cannot define a meaningful notion of crowding factor at door scale as the trains considered have corridor connections between coaches.

We note that in a different context with no timetable (Beijing subway Line 13) and thus a modeling solely based on passenger flows, Chu et al. [2015] already modeled the dwell time (equal to alighting/boarding time plus a fixed technical time in this context) based on boarding numbers per door  $B^i$ , together with global alighting numbers  $A$  and crowding factor  $C$  (which they turn into per-door quantities by diving by the number  $I$  of doors, i.e., using the unrealistic assumption of uniform distribution). Their data set was however of small scale (it was obtained by human observations).

## Outline of the article and summary of the results obtained

We describe the available data set and the railway context in Section 2: as discussed above, unlike most previous studies in the literature, it offers both railway operations variables and passenger flows variables. We then explain in Section 3 (and Appendix A) which machine-learning methods we consider to build, in a data-driven way, models for dwell time that can be used for all stations, all working days, all hours, and all trains. The modeling performance obtained by these models is discussed in Section 4, both at a global and at a “local” level. As summarized in our conclusions in Section 5, the main findings of our study are the following.

1. On average at a global level, the consideration of passenger flows variables on top of railway operations variables (only) decreases by about 0.5 s the modeling error on the observed dwell time based on mere railway operations variables.
2. However, it locally improves this modeling error in critical situations (while never deteriorating performance in non-critical situations) by sometimes up to 5 – 10 s on average: most notably, for late arrivals or for dense situations (when affluence is large).
3. More generally, the most influential variables to model the observed dwell time are the passengers flows for late arrivals, and the scheduled dwell time and deviation to scheduled arrival time for early trains.
4. The model built to obtain the global and local improvements mentioned above are based on a fully data-driven machine-learning technique called random forests, but it turns out that a closed-form linear regression model with multiplicative effects (by stations, ways and regimes of punctuality—trains that are early, on time, or late), that is also fully data driven, obtains a modeling performance that is only slightly worse.

We note that Appendix B discusses how robust our findings are, by considering variations around the main results.

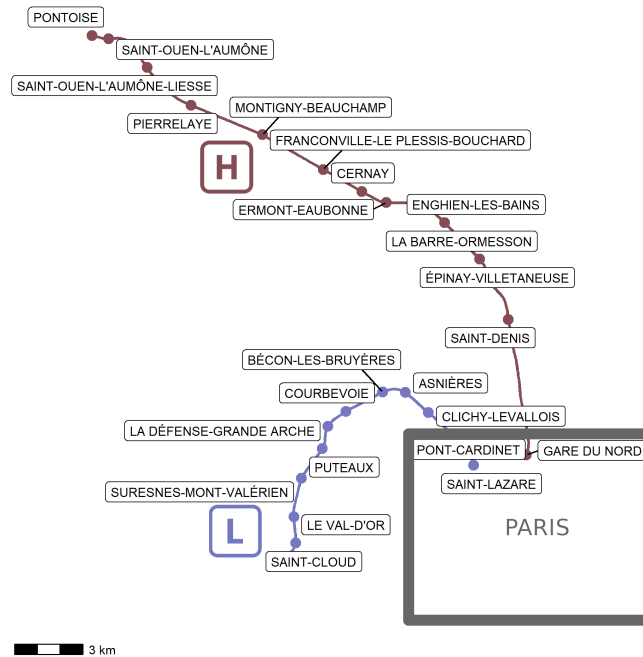


Figure 2: Branches of interest in lines H and L of the suburban railway network of the Greater Paris area.

## 2. Description of the data set and of the railway context

We consider a suburban railway network located in the Greater Paris area, and operated by Transilien SNCF. More precisely, we are interested in two different branches of lines H and L, featuring respectively 13 stations (11 without origin/terminus) and 11 stations (9 without origin/terminus); see Figure 2. We picked them because they are completely or almost completely run with Z50000-type rolling stocks equipped both with on-train monitoring recorder (OTMR) systems, which measure speed, arrival and departure times more precisely than track circuits, and with an automatic passenger counting (APC) system, which measures, for each door of the rolling stocks, the numbers of passengers boarding and alighting at each stop. Z50000-type rolling stocks on lines H and L are composed of 8 and 7 communicating coaches, respectively. For both lines, the mean seating and total capacities by coach equal respectively 59 seats and 119 passengers. The doors width is 1.96m. We are primarily interested in line L and postpone the study of line H in Appendix B.2; we explain in depth at the end of this section why we do so.

The data set spans 18 months, from March 15, 2018 to September 16, 2019. Each daily train ride comes with a unique ID, which we will refer to as the train ID. Three primary keys will therefore be used to refer to individual data points: the train number  $k$ , station  $s$  and day  $d$ : see Table 1. We merge the two data sources (OTMR data and APC data) by matching the triplets  $(k, s, d)$ . We keep all triplets present in both data sources and delete the other ones. We do not impose further restrictions, like the availability of all triplets  $(k, s', d)$  for a given day  $d$  and a given train ride  $k$  when  $s'$  spans the set of stations. The further pre-processing steps carried out are described below.

**Description of the variables.** The variables initially available for each triplet  $(k, s, d)$  are summarized in Table 2. Table 3 lists the variables created based on the ones of Table 2.

The railway operations variables of Table 2 consist first of observed and scheduled (theoretical) arrival times  $a^{\text{obs}}$  and  $a^{\text{theo}}$ , and actual (observed) and scheduled (theoretical) departure times  $d^{\text{obs}}$  and  $d^{\text{theo}}$ . Dwell times (observed and theoretical ones) are defined as the differences  $y^{\text{obs}} = d^{\text{obs}} - a^{\text{obs}}$  and  $y^{\text{theo}} = d^{\text{theo}} - a^{\text{theo}}$ . The variable of interest is the observed dwell time  $y^{\text{obs}}$ . All these variables

Table 1: Primary-key variables.

Variable	Notation
Train number	$k$
Station	$s$
Day	$d$

 Table 2: Railway operations variables (*top and middle parts of the table*, lower case) and passenger flow variables (*bottom part of the table*, upper case).

Variable	Domain and units	Notation
Variable of interest		
– Observed dwell time	$\{0 \text{ s}, 2 \text{ s}, \dots, 180 \text{ s}\}$	$y_{k,s,d}^{\text{obs}} = d_{k,s,d}^{\text{obs}} - a_{k,s,d}^{\text{obs}}$
Railway operations [Timetable data]		
– Theoretical (scheduled) arrival time	10 s steps	$a_{k,s,d}^{\text{theo}}$
– Theoretical (scheduled) departure time	10 s steps	$d_{k,s,d}^{\text{theo}}$
– Theoretical (scheduled) dwell time	$\{0 \text{ s}, 10 \text{ s}, \dots, 180 \text{ s}\}$	$y_{k,s,d}^{\text{theo}} = d_{k,s,d}^{\text{theo}} - a_{k,s,d}^{\text{theo}}$
Railway operations [OTMR data]		
– Observed arrival time	2 s steps	$a_{k,s,d}^{\text{obs}}$
– Observed departure time	2 s steps	$d_{k,s,d}^{\text{obs}}$
– Capacity (maximal passenger load)	$\{720; 922; 1,520; 1,844\}$	$c_{k,d}$
– Type	$\{\text{single}, \text{double}\}$	$t_{k,d}$
Passenger flows [APC data]		
– Alighting (number of passengers alighting)	$\{0, 1, \dots\}$	$A_{k,s,d}$
– Boarding (number of passengers boarding)	$\{0, 1, \dots\}$	$B_{k,s,d}$
– Load of the train after departure	$\{0, 1, \dots\}$	$L_{k,s,d}$

are indexed by triplets  $(k, s, d)$ . Two final variables are only indexed by  $(k, d)$  as they only depend on the train rides, not on the specific stations: the capacity  $c$  of the rolling stocks (the maximal passenger load allowed) and their types  $t$ . The type is “single” for single-unit trains and “double” for double-unit trains. The latter are mostly used during rush hours to increase capacity. Scheduled times were obtained from the timetables while other railway operations variables were picked in the OTMR data set.

Based on the variables just described, we may compute three other railway operations variables described in Table 3. The way  $w$  (that only depends on the train number  $k$ , i.e., on the ride) indicates whether the train goes from Paris to its suburbs, or from a suburban area to Paris. The deviation to the scheduled arrival time  $\Delta a$  is the difference  $a^{\text{obs}} - a^{\text{theo}}$  between the actual arrival time  $a^{\text{obs}}$  and the scheduled one  $a^{\text{theo}}$ . Three situations may actually arise in terms of punctuality, and this leads to a final, categorical, variable called “Regime of punctuality” and denoted by  $z$ . Early trains, i.e., trains for which  $a^{\text{obs}} < a^{\text{theo}}$ , will be tagged with  $z = 1$ . Late arrivals are tagged with  $z = 3$  and will refer to trains arriving after the scheduled departure time, i.e., for which  $a^{\text{obs}} > d^{\text{theo}}$ . (By definition, trains with a late arrival are not tied anymore by the constraint of not leaving before the scheduled departure

Table 3: Processed variables (with the same breakdown as in Table 2).

Variable	Domain and units	Notation
Railway operations		
– Way	$\{0,1\}$	$w_k$
	$w_k = 1$ if train $k$ goes from Paris to suburbs, $= 0$ from suburbs to Paris	
– Deviation to scheduled arrival time	$[-600 \text{ s}, 600 \text{ s}]$	$\Delta a_{k,s,d} = a_{k,s,d}^{\text{obs}} - a_{k,s,d}^{\text{theo}}$
– Regime of punctuality	$\{1, 2, 3\}$	$z_{k,s,d}$
	$= 1$ if train is early, $a_{k,s,d}^{\text{obs}} < a_{k,s,d}^{\text{theo}}$ ;	
	$= 2$ if on time, $a_{k,s,d}^{\text{theo}} \leq a_{k,s,d}^{\text{obs}} \leq d_{k,s,d}^{\text{theo}}$ ;	
	$= 3$ if late, $d_{k,s,d}^{\text{theo}} < a_{k,s,d}^{\text{obs}}$	
Passenger flows		
– Crowding factor	$[0, 2]$	$C_{k,s,d} = L_{k,s,d}/c_{k,s,d}$
– Affluence at the critical door	$\{0, 1, \dots\}$	$M_{k,s,d}$

time.) The third category  $z = 2$  corresponds to trains on time, for which  $a^{\text{theo}} \leq a^{\text{obs}} \leq d^{\text{theo}}$ .

We only use some of the passenger flows variables available. Indeed, the APC data set reports the numbers of passengers alighting and boarding for each train at each station, globally (variables  $A$  and  $B$ ) and for each door  $i$  (variables  $A^i$  and  $B^i$ ). All these variables are indexed by triplets  $(k, s, d)$ . The values available in the APC data set are not raw data but were obtained after some pre-processing ensuring consistency (e.g., total numbers  $A$  and  $B$  are the sums of the by-door quantities  $A^i$  and  $B^i$ ; the sums of the boarding numbers along the ride equal the sums of the alighting numbers). Such a pre-processing is required because of the measurement noise due to the infra-red sensor.

To avoid considering too many variables, we only use the total numbers  $A$  and  $B$  of alighting and boarding passengers (Table 2), as well as the affluence at the critical door, defined as the maximal number, over the  $I$  doors, of alighting and boarding passengers at a given door  $i$ :

$$M = \max_{i=1,\dots,I} A^i + B^i.$$

The affluence at the critical door  $M$  is thus a processed variable (Table 3). A second processed variable is the crowding factor  $C = L/c$ , defined as the ratio between the load  $L$  and the maximal capacity  $c$ . We observe some values of  $C$  larger than 1 in the data set.

All in all, our data set is a unique combination of typically accessible railway operations variables with rich passenger flows variables. The closest data set in the literature is the one of Cornet et al. [2019], which however does not contain by-door measures of affluence.

**Modeling vs. prediction.** The focus of the present article is only on modeling dwell time based on the explanatory variables described above. The passenger flows variables are available in real time (i.e., right after the train leaves a station) while the railway operations variables are only known with some delay (they are not transmitted in real time). To move from modeling to prediction we would need to predict passenger flows variables for the next station and know the railway operations variables in real time (e.g., know the deviation  $\Delta a$  to scheduled arrival when the train stops and the passenger exchange starts taking place). It turns out that the APC data set actually contains some railway operations variables, measured in real time, but they are less reliable than the OTMR measurements. In any case, we would need predictions for passengers flows. This is why the focus of the present article is only on modeling (i.e., explaining the determinants of dwell time) and not on forecasting.



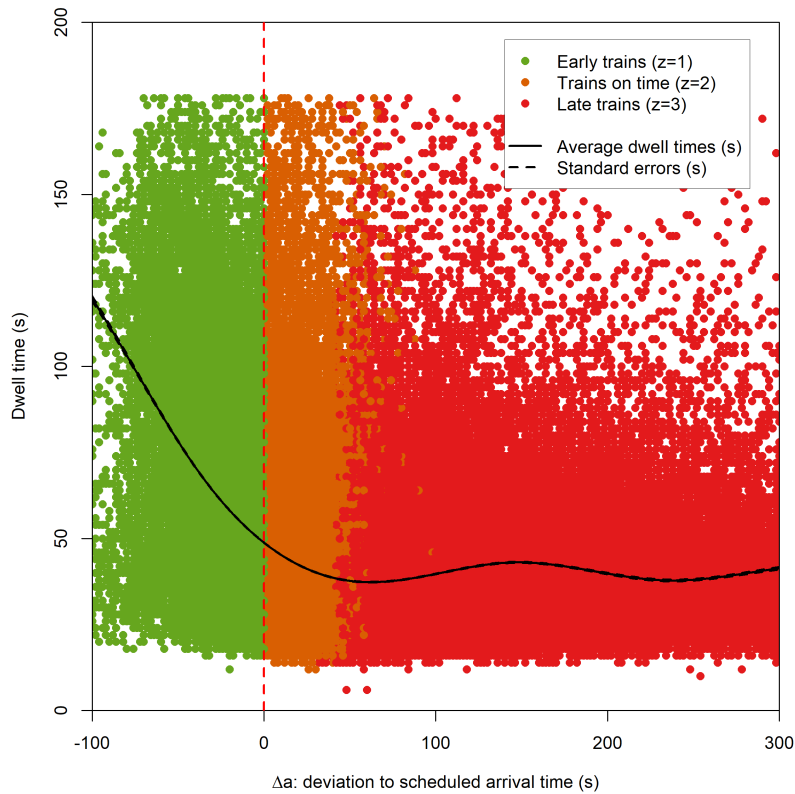


Figure 3: Observed dwell times ( $y$ -axis, seconds) by deviations  $\Delta a$  to scheduled arrival times ( $x$ -axis, seconds); we also report average dwell times and standard errors thereof, based on some generalized additive modeling. Three regimes are considered: early trains, trains on time, late trains.

**Further pre-processing of the data / Data volume.** On top of the pre-processing described above, which consisted of keeping only observations and variables relative to triplets  $(k, s, d)$  present in both data sources (OTMR and APC), we performed some data cleaning. First, we deleted triplets  $(k, s, d)$  corresponding to anomalous situations: when the observed dwell time  $y_{k,s,d}^{\text{obs}}$  is longer than 180 seconds (as Cornet et al. [2019], Dueker et al. [2004] did) or when current cumulative delays on the ride are larger than 10 minutes.

Doing so, we get more than 350,000 observations for line L and 416,000 for line H.

**Railway contexts: line L is more important than line H.** We mainly report results for line L in the next sections and will only briefly discuss line H later on, in Section B.2. We explain here the several reasons why we favor line L over line H in our study.

First, the passenger flows on line L are more varied than on line H. On line H, most of the passenger flows take place at terminus, while on line L, there exist major intermediate stations (like La Défense Grande Arche) also generating major passenger flows. The average passenger volumes vary from 1,300 to 37,000 passengers per day on the considered branch of line L.

Second, the railway operations are more challenging on line L than on line H. On the one hand, the traffic on line L is more dense than the one of line H for stations distant from Paris, on peak hours: typically, a train every 5 minutes on line L versus every 15 minutes on line H. (For stations close to Paris, the density is similar, with about 22 to 24 trains per hour, that is, a train every 2 to 3 minutes.) On the other hand, lines L and H also differ in terms of punctuality, with a greater variety of situations for line L: most of the train rides on line H end up being on time or late, while there is also a significant fraction of early train rides on line L on top of on-time and late train rides.

Figure 3 depicts the observed dwell times, as well as the averages thereof, on the considered branch of line L, by deviations  $\Delta a$  to scheduled arrival times. The averages and standard errors were obtained by a generalized additive method modeling based on 10 cubic splines, see Wood [2006]. We build confidence intervals around the averages of half-widths  $\pm 2$  standard errors. Finally, boarding volumes on line L are sufficiently higher than on line H to result in larger crowding factors, despite the higher density of trains.

### 3. Methods

We model the observed dwell times  $y_{k,s,d}^{\text{obs}}$  as a stochastic function of *some* of the variables described in Tables 2 and 3, namely,

$$y_{k,s,d}^{\text{obs}} = f(s, w_k, t_{k,d}, y_{k,s,d}^{\text{theo}}, \Delta a_{k,s,d}, z_{k,s,d}, A_{k,s,d}, B_{k,s,d}, C_{k,s,d}, M_{k,s,d}) + \varepsilon_{k,s,d}, \quad (1)$$

where  $f$  is some deterministic function and the additive residual terms  $\varepsilon_{k,s,d}$  are random variables (assumptions thereon will depend on each method used, see below). We justify below the choice of the variables used in Equation (1).

We are interested in some statistical modeling and do not propose simulation or probabilistic models (as did D’Acierno et al. [2017] or Cornet et al. [2019]). Also, we model directly  $y_{k,s,d}^{\text{obs}}$ , and not  $y^{\text{obs}} - y^{\text{theo}}$ , as we want to separate the respective information provided by passenger flows variables and railway operations variables. See Appendix B.1 for more details and a report of the performance obtained by rather modeling  $y^{\text{obs}} - y^{\text{theo}}$ .

#### 3.1. Justification of the variables used

First, for each Transilien network branch, the combination of the station  $s$  and the way  $w_k$  indicates on which specific platform the train will stop. This is important in light of studies like the one by Daamen et al. [2008], who confirmed the major impact of platform design (stepping gap, height difference, etc.) on the lighting and boarding time.

Now, out of the many railway operations variables available, we only use  $y_{k,s,d}^{\text{theo}}, \Delta a_{k,s,d}, z_{k,s,d}, t_{k,d}$ . We do so because we want to build a model that can be easily grasped. First, the scheduled dwell time  $y^{\text{theo}}$  of course provides some benchmark on the expected dwell times; this piece of information is typically used in modelings, in some direct or indirect way, see, among others, Kecman and Goverde [2015] and Li et al. [2016]. We already explained that Hansen et al. [2010] showed how important the deviation to scheduled arrival time  $\Delta a$  is to explain the dwell times, and Figure 3 illustrated it. We build regimes of punctuality  $z$  based on  $\Delta a$  (see Table 3) to isolate unconstrained dwell times (for late trains,  $z = 3$ ) from dwell times constrained by the scheduled departure time. In particular, we expect that early trains which do not face too high an affluence need to wait till the scheduled departure time and hence, have an observed dwell time equal to  $y^{\text{theo}} + |\Delta a|$ , the scheduled dwell time plus how early they were. On the contrary, we expect that drivers of late trains will try to shorten dwell times as much as possible.

Finally, the type  $t$  of train is also important: it provides an indirect idea of the expected affluence, as double-unit trains are only used when necessary; this idea is inspired from Kecman and Goverde [2015]. It may also help because double-unit trains and single-unit trains occupy different shares of the platform, and we already mentioned how important the design of the platform is. However, we chose not to consider the other railway operations variables, that should either be irrelevant (scheduled departure time, scheduled and observed arrival times should not convey any information beyond what is already contained in  $\Delta a$  and  $y^{\text{theo}}$ ) or be future variables (the observed departure time is basically what is to be modeled).

As far as passenger flows variables are considered, we consider them all except the load  $L$  of the train, as the latter only has a meaning relative to the train capacity—hence the crowding factor  $C$ .

**Remark: no auto-regressive modeling.** Our aim is to model dwell times based on the current context (state of railway operations, affluence, etc.) and determine which elements of this context have the most important influence on dwell time. Our aim is not to forecast dwell times. Therefore, we do not consider auto-regressive-type models, i.e., do not include variables like  $y_{k-1,s,d}^{\text{obs}}$  or  $y_{k,s-1,d}^{\text{obs}}$  in the modeling of  $y_{k,s,d}^{\text{obs}}$ . See Li et al. [2016] and Pritchard et al. [2021] for such modelings.

**Subsets of variables: RO, PF, M.** As we want to determine which variables are most influential, we group them in two groups and a half. We always use  $s$  and  $w_k$  and cluster the rest of the variables into

- Railway operations variables [short-hand notation “RO”]:  $y_{k,s,d}^{\text{theo}}$ ,  $\Delta a_{k,s,d}$ ,  $z_{k,s,d}$ ,  $t_{k,d}$ ;
- Passenger flows variables [short-hand notation “PF”], not taking into account the affluence at the critical door:  $A_{k,s,d}$ ,  $B_{k,s,d}$ ,  $C_{k,s,d}$ ;
- Affluence at the critical door [short-hand notation “M”]:  $M_{k,s,d}$ .

We will actually run our methods with  $s$ ,  $w_k$  and either just RO variables, or just PF variables, or RO+PF variables, or RO+PF+M variables.

### 3.2. One model for all stations, all working days, all hours, and all trains

We restrict our attention to working days (i.e., Mondays to Fridays that are not public holidays nor belong to school holidays). We do so because we want to assess the impact of passenger flows on dwell time, and these flows are limited on non-working days. Our second aim is to build models suitable for all stations, all working days, at all hours and for all trains simultaneously, using only variables  $s$  (the station) and  $w_k$  (the way of train  $k$ ) to locally adapt the model.

We however do not try to provide a general model that would work for all train networks (as in Harris and Anderson [2007] and Li et al. [2016]), but rather provide a general methodology to adjust specific dwell-time models for each (sub)network suitably equipped in terms of monitoring devices (APC and OTMR ones).

Linear regression models (see, among others, Lam et al. [1998], Harris and Anderson [2007], Palmqvist et al. [2020]) are a popular such general methodology, that leads to easily interpretable models. Machine-learning models were later considered (see, among others, Kecman and Goverde [2015]) to improve the accuracy of the modeling based on linear regressions, at the cost of building black-box models. We describe linear regression models in Section 3.3, and then some machine-learning methods: random forests and gradient boosting in Section 3.4, and neural networks in Section 3.5. We provide concise such descriptions but refer interested readers to Hastie et al. [2009] for deeper expositions. Finally, we explain in Section 3.6 how to tune these methods (on a train set) and evaluate them in a fair way (on a test set).

### 3.3. Linear regression models (with additive or multiplicative effects)

The simplest version of linear regression models uses an affine function  $f$  in Equation (1). In  $f$ , the quantitative variables, namely,  $y_{k,s,d}^{\text{theo}}$  and  $\Delta a_{k,s,d}$  when RO variables are considered,  $A_{k,s,d}$ ,  $B_{k,s,d}$ ,  $C_{k,s,d}$  when PF variables are considered, and  $M_{k,s,d}$  for the M variable, are each associated with slope coefficients denoted by  $\beta^{(y)}$ ,  $\beta^{(\Delta a)}$ ,  $\beta^{(A)}$ ,  $\beta^{(B)}$ ,  $\beta^{(C)}$ , and  $\beta^{(M)}$ , respectively. As for the categorical variables, namely,  $s$  and  $w_k$  in all cases, and  $z_{k,s,d}$  and  $t_{k,d}$  when RO variables are considered, we include them by considering  $K - 1$  indicator variables, where  $K$  denotes the number of modalities taken. For instance, we denote by  $S$  the number of stations and index them by  $1, \dots, S$ ; we take the last station as a reference modality and the regression function  $f$  thus features  $S - 1$  coefficients  $\beta_{s'}^{\text{station}}$ , where  $s' \in \{1, \dots, S - 1\}$ . Similarly, for  $t$  and  $w$ , which both only take two values, we take the

modalities “single” and  $w = 0$  (from suburbs to Paris) as reference values, and the regression function  $f$  features the coefficient  $\beta^{\text{type}}$  and  $\beta^{\text{way}}$ . Finally, for the variable  $z$  which take three modalities, we pick  $z = 2$  (trains on time) as a reference value and thus have two coefficients  $\beta^{\text{early}}$  and  $\beta^{\text{late}}$  for inclusion in  $f$ . We denote the global intercept by  $\beta^0$ . All in all, with the simultaneous consideration of the RO, PF, and M variables, we use in Equation (1)

$$\begin{aligned}
 & f(s, w_k, t_{k,d}, y_{k,s,d}^{\text{theo}}, \Delta a_{k,s,d}, z_{k,s,d}, A_{k,s,d}, B_{k,s,d}, C_{k,s,d}, M_{k,s,d}) & (2) \\
 & = \left. \beta^0 + \beta^{\text{way}} \mathbb{1}_{[w_k=1]} + \sum_{s'=1}^{S-1} \beta_{s'}^{\text{station}} \mathbb{1}_{[s=s']} \right\} \text{ in all cases} \\
 & \quad + \left. \beta^{(\Delta a)} \Delta a_{k,s,d} + \beta^{(y)} y_{k,s,d}^{\text{theo}} + \beta^{\text{type}} \mathbb{1}_{[t_{k,d}=\text{double}]} + \beta^{\text{early}} \mathbb{1}_{[z_{k,s,d}=1]} + \beta^{\text{late}} \mathbb{1}_{[z_{k,s,d}=3]} \right\} \text{ RO variables} \\
 & \quad + \left. \beta^{(A)} A_{k,s,d} + \beta^{(B)} B_{k,s,d} + \beta^{(C)} C_{k,s,d} \quad + \beta^{(M)} M_{k,s,d} \right\} \text{ PF+M variables}
 \end{aligned}$$

If we only use some of these variables, we suppress some terms in the equation above (e.g., the second line if we only use the PF+M variables; or the term  $\beta^{(M)} M_{k,s,d}$  if we use the RO+PF variables).

**Linear regression with additive effects.** We call the model above the linear regression with additive effects. It features  $S + 1$  coefficients in all cases, plus 5 coefficients when RO variables are included, 3 when PF variables are used, and 1 for the M variable, respectively. This leads to the numbers of coefficient stated in the first line of Table 4.

**Multiplicative effect of  $\Delta a$  by  $z$ .** To take into consideration the special relation between the dwell time and the deviation to scheduled arrival time (see Figure 3), we provide a different affine modeling in terms of  $\Delta a_{k,s,d}$  for each value of  $z_{k,s,d}$ . Put differently, instead of a single slope coefficient  $\beta^{(\Delta a)}$  in front of  $\Delta a_{k,s,d}$ , we provide a breakdown by punctuality  $z_{k,s,d} \in \{1, 2, 3\}$  and use three different slope coefficients  $\beta_1^{(\Delta a)}, \beta_2^{(\Delta a)}, \beta_3^{(\Delta a)}$ . We do this on top of setting different intercept levels through the consideration of  $\beta^{\text{early}}$  and  $\beta^{\text{late}}$ . That is, with the simultaneous consideration of the RO, PF, and M variables, we use in Equation (1)

$$\begin{aligned}
 & f(s, w_k, t_{k,d}, y_{k,s,d}^{\text{theo}}, \Delta a_{k,s,d}, z_{k,s,d}, B_{k,s,d}, A_{k,s,d}, C_{k,s,d}, M_{k,s,d}) & (3) \\
 & = \left. \beta^0 + \beta^{\text{way}} \mathbb{1}_{[w_k=1]} + \sum_{s'=1}^{S-1} \beta_{s'}^{\text{station}} \mathbb{1}_{[s=s']} \right\} \text{ in all cases} \\
 & \quad + \left. \sum_{z \in \{1,2,3\}} \mathbb{1}_{[z_{k,s,d}=z]} \beta_z^{(\Delta a)} \Delta a_{k,s,d} \right\} \text{ RO variables, new part: interaction between } \Delta a \text{ and } z \\
 & \quad + \left. \beta^{(y)} y_{k,s,d}^{\text{theo}} + \beta^{\text{type}} \mathbb{1}_{[t_{k,d}=\text{double}]} + \beta^{\text{early}} \mathbb{1}_{[z_{k,s,d}=1]} + \beta^{\text{late}} \mathbb{1}_{[z_{k,s,d}=3]} \right\} \text{ RO variables, no change} \\
 & \quad + \left. \beta^{(A)} A_{k,s,d} + \beta^{(B)} B_{k,s,d} + \beta^{(C)} C_{k,s,d} \quad + \beta^{(M)} M_{k,s,d} \right\} \text{ PF+M variables}
 \end{aligned}$$

We call the model above the linear regression with a multiplicative effect of  $\Delta a$  by  $z$ . When RO variables are considered, it contains two additional coefficients with respect to the model with additive effects and does not differ from the latter when RO variables are omitted; see the second line of Table 4.

**Additional multiplicative effects.** We may have the slope coefficients, as well as the intercepts, vary by pairs  $(s, z)$  or even, triplets  $(s, w, z)$  to locally tailor the model to the stations and to the

	Variables used			
	PF	RO	RO+PF	RO+PF+M
Additive effects	14	16	19	20
Multiplicative effect of $\Delta a$ by $z$	14	18	21	22
Multiplicative effects by $(s, w, z)$	$\geq 180$	$\geq 120$	$\geq 300$	$\geq 360$

Table 4: Numbers of coefficients of the various linear regressions considered, for line L (for which there are  $S = 10$  stations).

regime of punctuality; i.e., with PF variables, the regression function  $f$  would, for instance, feature terms like

$$\sum_{\substack{s' \in \{1, \dots, S\} \\ w \in \{0, 1\} \\ z \in \{1, 2, 3\}}} \mathbb{1} \left[ \begin{array}{l} s=s', \\ w_k=w, \\ z_{k,s,d}=z \end{array} \right] \beta_{s,w,z}^{(A)} A_{k,s,d} + \sum_{\substack{s' \in \{1, \dots, S\} \\ w \in \{0, 1\} \\ z \in \{1, 2, 3\}}} \mathbb{1} \left[ \begin{array}{l} s=s', \\ w_k=w, \\ z_{k,s,d}=z \end{array} \right] \beta_{s,w,z}^{(B)} B_{k,s,d} + \sum_{\substack{s' \in \{1, \dots, S\} \\ w \in \{0, 1\} \\ z \in \{1, 2, 3\}}} \mathbb{1} \left[ \begin{array}{l} s=s', \\ w_k=w, \\ z_{k,s,d}=z \end{array} \right] \beta_{s,w,z}^{(C)} C_{k,s,d}$$

instead of  $\beta^{(A)} A_{k,s,d} + \beta^{(B)} B_{k,s,d} + \beta^{(C)} C_{k,s,d}$ . For multiplicative effects by triplets, we end up with models with at least  $6S$  coefficients per quantitative variable considered (the total number of coefficient depending on the specific dependencies considered for the intercepts); see the third line of Table 4. We tried many formulations and all get a similar performance.

The linear models discussed in this section are reference models and are mostly of interest for the sake of comparison with more complex, machine-learning, methods, which often exhibit a better performance, at the cost of not leading to statistical models, i.e., closed-form relationships that may be interpreted. We consider two methods based on regression trees, which we describe now, and one on neural networks, which we describe later.

### 3.4. Machine-learning methods based on regression trees: random forests and gradient boosting

Machine-learning methods based on regression trees were already considered by the literature on transportation systems: Kecman and Goverde [2015] used random forests to model dwell time for trains circulating between the Hague and Rotterdam, based on similar railway operations (RO) variables as we consider in this article; Ding et al. [2016] used gradient boosting and were interested in short-term metro ridership forecasting (next 15 minutes) on three major Beijing stations. Zhang and Haghani [2015] considered both methods to forecast car travel time on a motorway section in Maryland; in their study, boosting methods slightly outperformed random forests. All three references present in details random forests and gradient boosting and do so by first introducing regression trees. We follow the same path.

**Concept of a regression tree.** We denote by  $\mathbf{X}_{k,s,d}$  the feature vectors, i.e., the vectors of variables available for each triplet  $(k, s, d)$ . These variables were described in Section 3.1, except that we replace the non-binary categorical variables  $s$  and  $z$ , which have  $S$  and 3 modalities, by  $S$  and 3 binary variables, respectively<sup>1</sup>. Table 5 indicates the size of  $\mathbf{X}_{k,s,d}$  depending on the subset of variables used, by distinguishing components that are quantitative variables and the ones that are given by binary categorical variables.

<sup>1</sup>Doing so, we only consider additive effects, as in (2). We also tested—but do not discuss here—partially multiplicative effects, for instance, replacing the component  $\Delta a_{k,s,d}$  of  $\mathbf{X}_{k,s,d}$  by the three variables  $\Delta a_{k,s,d} \mathbb{1}_{[z_{k,s,d}=z]}$ , for  $z \in \{1, 2, 3\}$ , that were used in (3). We did not observe significant gains in performance and were not surprised: regression-tree-based methods are per se able to deal with complex interactions between features and output (dwell time).

Size of $\mathbf{X}$	Variables used			
	PF	RO	RO+PF	RO+PF+M
Quantitative components	3	2	5	6
Binary components	11	15	15	15
Total number	14	17	20	21

Table 5: Size of the feature vectors  $\mathbf{X}_{k,s,d}$  for line L (for which there are  $S = 10$  stations), depending on the subsets of variables considered.

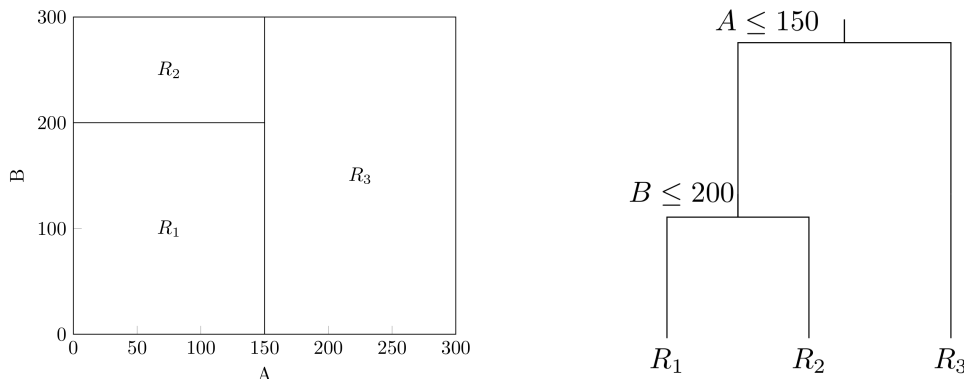


Figure 4: Toy example of a regression tree: the partition with 3 elements in terms of values of the variables  $A$  and  $B$  (left) and the associated binary tree (right).

A regression tree relies on a (hierarchically organized) partition of the feature space into finitely many regions  $\mathcal{R}_1, \dots, \mathcal{R}_R$  defined by thresholds on the components of feature vectors  $\mathbf{X}$ . Indeed, the partition stems from a binary tree, where the two children of each node are defined by a threshold level on a quantitative variable, or the values 0 and 1 of a binary variable. A toy illustration with a two-level hierarchy and its associated partition is provided in Figure 4: the threshold at the root node is based on the number  $A$  of passengers alighting and uses the value 150, and there is a second level for the left child, which is based on the number  $B$  of passengers boarding and uses the threshold value 200. A regression tree is built on train data  $\mathbf{X}_{k,s,d}$  in a greedy manner through successive refinements of the current binary regression tree until the refinement stops, i.e., when a node is declared a leaf. The variable and associated threshold at each node are determined by considering all possible choices thereof and by picking the pair that leads to the smallest in-sample square error for the corresponding augmented regression tree. We will consider two stopping rules, both aiming to avoid over-fitting the data. The first rule is that if one of the created children node contains fewer than 5 observations, the refinement actually does not occur, and the node at hand is declared a leaf. The second rule is to construct complete binary trees of a fixed depth (where the depth of a tree is defined by the number of nodes along the longest path from the root node down to the farthest leaf), i.e., stop refining when a certain depth is reached. This concludes the description of the construction of a regression tree; we recall that it may be identified with a hierarchical partition  $\mathcal{R}_1, \dots, \mathcal{R}_R$  of the feature vectors  $\mathbf{X}$ .

Then, when a new feature vector  $\mathbf{X}$  is to be handled, the method first identifies in which region  $\mathcal{R}(\mathbf{X})$  of the partition  $\mathcal{R}_1, \dots, \mathcal{R}_R$  this feature vector lies. The modeled dwell time  $f(\mathbf{X})$  for this new feature vector  $\mathbf{X}$  finally equals the empirical average of the values  $y_{k,s,d}^{\text{obs}}$  of those feature vectors  $\mathbf{X}_{k,s,d}$  that lie in the same region  $\mathcal{R}(\mathbf{X})$ , if there is at most one such vector (otherwise, an arbitrary value is output):

$$f(\mathbf{X}) = \frac{1}{\sum_{k,s,d} \mathbb{1}_{[\mathbf{X}_{k,s,d} \in \mathcal{R}(\mathbf{X})]}} \sum_{k,s,d} y_{k,s,d}^{\text{obs}} \mathbb{1}_{[\mathbf{X}_{k,s,d} \in \mathcal{R}(\mathbf{X})]}.$$

The response function  $f$  is piecewise constant (it is constant over each member  $\mathcal{R}_r$  of the partition).

One major problem of regression trees comes from their instability, which is due to their hierarchical construction: small variations in data may affect the choices made in the higher nodes and result in drastically different final results. To overcome this issue, two methods were proposed by the machine-learning literature: random forests and gradient boosting with regression trees. Both are ensemble methods using many trees of small depth to avoid over-fitting and to reduce the variances of regression trees.

**Random forests.** Random forests were introduced by Breiman [2001], they consist of generating (partially at random)  $T$  regression trees  $f^{(1)}, \dots, f^{(T)}$  as described above with the first stopping rule, and by resorting to the response function given by the average of these trees:

$$f(\mathbf{X}) = \frac{1}{T} \sum_{t=1}^T f^{(t)}(\mathbf{X}).$$

The number  $T$  of random trees is large, and the rationale behind the average is that model errors are therefore expected to compensate each others. Kecman and Goverde [2015] was the first to use random forests for dwell time estimation, using RO variables. We explain below how the random trees  $f^{(t)}$  are generated and how their number  $T$  is chosen.

Two sources of randomness are introduced to construct each given tree  $f^{(t)}$ : first, the data sample used to build  $f^{(t)}$  is obtained by bootstrapping (i.e., by sampling with replacement into the original data), and second, to grow the tree from this bootstrapped sample, only  $m$  variables (picked at random) out of the  $p$  variables are used. These artificial sources of randomness are useful to create independence between the trees  $f^{(1)}, \dots, f^{(T)}$ .

We implemented random forests using the R package `ranger` (see Wright and Ziegler, 2017; it is better suited to large data sets than, e.g., the `randomForest` package). It uses two parameters, `ntree` for the the number of trees  $T$  and `mtry` for  $m$  the number of variables chosen at each split. Both are tuned by cross validation, see Section 3.6. The bootstrapped data samples are of the same size as the original data set.

**Gradient boosting with regression trees.** While random forests rely on a compensation of individual errors through bagging, gradient boosting (Friedman, 2001) iteratively builds weighted sums of regression trees by focusing on the observations with the highest model errors. The regression trees successively picked for the weighted sums are thus not independent from each other.

More precisely, the basic idea of gradient tree boosting is to consider a set  $\mathcal{F}$  of possible binary trees and start with an arbitrary tree  $f^{(1)} \in \mathcal{F}$ ; in the chosen implementation,  $\mathcal{F}$  is the set of all complete binary trees of depth 6. At each iteration  $t \geq 2$ , we then construct a weighted sum  $f^{(t)}$  of regression trees by first considering the modeling errors

$$e_{k,s,d}^{(t-1)} = y_{k,s,d}^{\text{obs}} - f^{(t-1)}(\mathbf{X}_{k,s,d})$$

associated with the weighted sum  $f^{(t-1)}$  of the previous step, by picking the best tree  $g^{(t)} \in \mathcal{F}$  to model these errors, i.e.,

$$g^{(t)} \in \operatorname{argmin}_{f \in \mathcal{F}} \sum_{k,s,d} \left( e_{k,s,d}^{(t-1)} - f(\mathbf{X}_{k,s,d}) \right)^2,$$

by picking the best step size  $\alpha^{(t)} \in \mathbb{R}$  to model these errors given  $g^{(t)}$ , i.e.,

$$\alpha^{(t)} \in \operatorname{argmin}_{\alpha \in \mathbb{R}} \sum_{k,s,d} \left( e_{k,s,d}^{(t-1)} - \alpha g^{(t)}(\mathbf{X}_{k,s,d}) \right)^2,$$

and by finally outputting

$$f^{(t)} = f^{(t-1)} + \eta \alpha^{(t)} g^{(t)},$$

where we consider a shrinkage parameter  $\eta$ . The optimizations on  $f \in \mathcal{F}$  and  $\alpha \in \mathbb{R}$  are performed successively and not simultaneously because of computational issues. The procedure stops after  $T$  rounds and the final modeling  $f$  equals

$$f = f^{(T)} = f^{(1)} + \eta \sum_{t=2}^T \alpha^{(t)} g^{(t)}.$$

Both  $\eta$  and  $T$  are parameters to be set by the user.

As indicated above, these are only the high-level ideas behind the specific method used, namely, XGBoost by Chen and Guestrin [2016], which relies on two decades of advances in boosting and tree methods. We use the R package `xgboost`. The XGBoost method may be finely tuned through a few dozens of parameters, including the choice of the tree set  $\mathcal{F}$ ; we use the default values, except for  $T$  and  $\eta$  (which correspond to the parameters `nrounds` and `eta`, respectively), which we tune by cross validation, see Section 3.6. It is a common choice (both in machine learning competitions and in the transportation literature, see Ding et al., 2016) to focus mostly on these two parameters. They work hand in hand: on the one hand, large values of  $T$  and  $\eta$  lead to over-fitting (i.e., building a model too close to historical data with poor generalization guarantees), on the other hand, for XGBoost to “converge”—i.e., be such that  $f^{(t)}$  does not change much as  $t$  approaches  $T$ —the shrinkage parameter  $\eta$  and  $T$  need to be small enough. All in all, a good balance between  $T$  and  $\eta$  should be achieved.

### 3.5. Feed-forward neural networks

Artificial neural networks (see Goodfellow et al., 2016) are a popular method for designing highly non-linear predictors, in all fields of science and engineering, including transportation research. They are considered in transportation research about public transports with relatively simple architectures, typically based on at most one hidden layer. For instance, Yaghini et al. [2013] used such simple neural networks to classify train delays for Iranian railways, while Amita et al. [2015] did so to predict bus running times in Dehli based on GPS data. In traffic literature more complex architecture are often considered, as did Li et al. [2018] for the forecasting of road traffic flows on two data sets from California highways. They compare two methods, a dense feed-forward neural network with two hidden layers of 256 nodes each and a more complex diffusion convolution recurrent neural network. As we face a public-transport application, we do not consider the latter method and only proceed with feed-forward neural networks.

The mentioned references all consider different architectures for their feed-forward neural networks: to a great extent, the choice of the architecture of a neural network is subjective and relies on engineering experience. However, in this work, we consider the number of hidden layers  $H$  and the number  $N$  of nodes per layer as tuning parameters (to be chosen through cross validation, see Section 3.6).

The architecture considered for our feed-forward networks is depicted in Figure 5; it is composed of an input layer, of  $H$  hidden dense layers (each with  $N$  nodes), and of an output layer. It corresponds to inductively constructing the modeling  $f(\mathbf{X}_{k,s,d})$  as follows. The output function  $f^{(1)}$  of the first layer  $h = 1$  takes a  $p$ -dimensional vector  $\mathbf{X} = (X_1, \dots, X_p)$  as argument, where  $p$  is provided by Table 5, and outputs a vector of length  $N$ , based on real weights  $\theta_{j,n,0}$ , on intercepts  $b_{n,0}$ , and on the



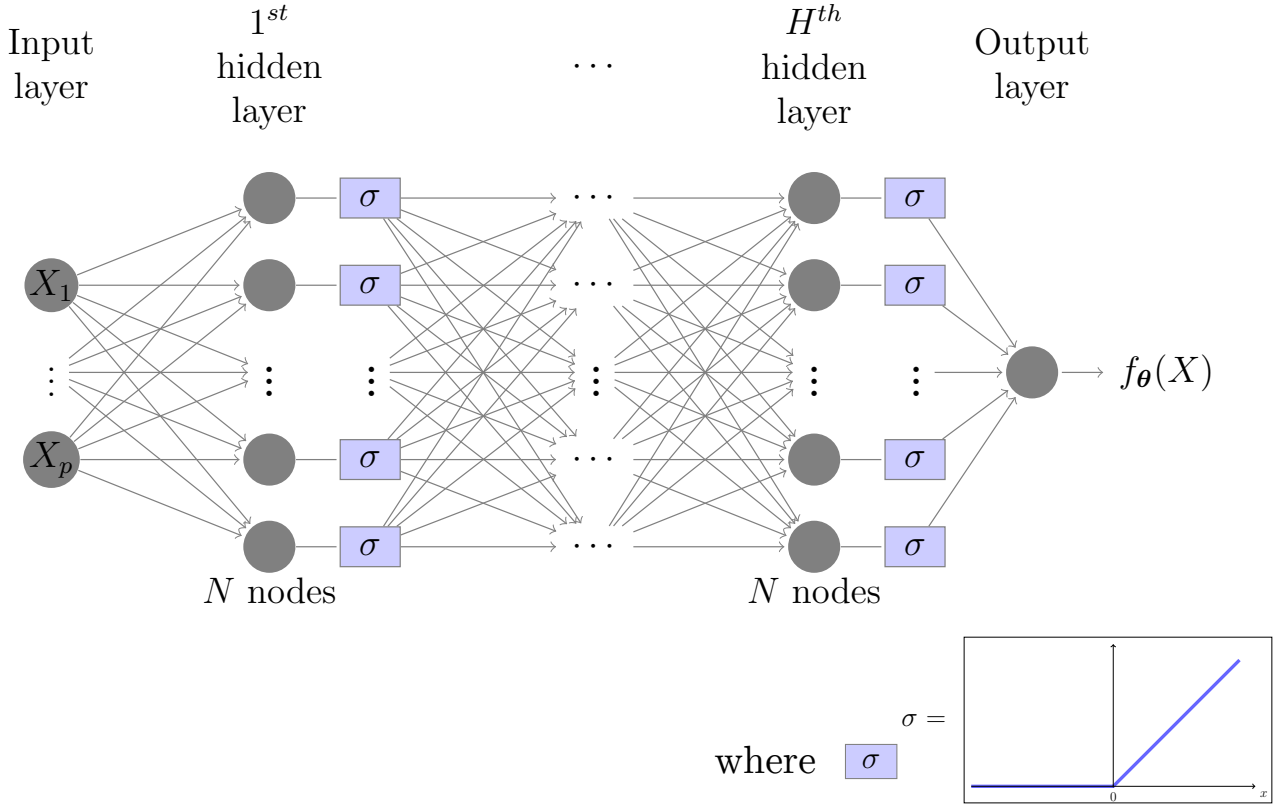


Figure 5: Architecture of the feed-forward networks considered; the  $\sigma$  boxes correspond to the application of the rectified linear unit (ReLU) activation function  $\sigma(x) = \max\{x, 0\}$  depicted at the bottom.

so-called rectified linear unit (ReLU) activation<sup>2</sup> function  $\sigma(x) = \max\{x, 0\}$ :

$$f^{(1)}(\mathbf{X}) = \left( \sigma \left( b_{n,0} + \sum_{j=1}^p \theta_{j,n,0} X_j \right) \right)_{n \in \{1, \dots, N\}}.$$

The hidden layers  $h \in \{2, \dots, H\}$  are then each associated with a function  $f^{(h)}$  based on the components  $f_{n'}^{(h-1)}$  of  $f^{(h-1)}$ , on real weights  $\theta_{n',n,h}$  of the arc connecting node  $n'$  of hidden layer  $h-1$  and node  $n$  of hidden layer  $h$ , on intercepts  $b_{n,h}$ , and on the ReLU activation function  $\sigma$ :

$$f^{(h)}(\mathbf{X}) = \left( \sigma \left( b_{n,h} + \sum_{n'=1}^N \theta_{n',n,h} f_{n'}^{(h-1)} \right) \right)_{n \in \{1, \dots, N\}}.$$

The final function  $f_{\theta}$  is then based on  $f^{(H)}$  and on a final series of real weights  $\theta_{n,H+1}$  and on a final intercept  $b_{H+1}$ :

$$f_{\theta} = b_{H+1} + \sum_{n=1}^N \theta_{n,H+1} f_n^{(H)};$$

here, we collected all parameters (weights and intercepts, of all layers) into a vector denoted by  $\theta$ .

<sup>2</sup>Li et al. [2018] also use the ReLU activation function while Yaghini et al. [2013] and Amita et al. [2015] use instead a sigmoid activation function  $x \mapsto 1/(1 + e^{-x})$ . We picked the ReLU activation function mostly because of its popularity, as asserted by Goodfellow et al. [2016].

Table 6: Grids for picking the hyperparameters (a.k.a. tuning parameters) on the train set.

Method	Hyperparameter #1	Hyperparameter #2
Random forests	$m \in \{1, 2, \dots, 15\}$	$T \in \{1, 10, 50, 100, 500, 1000, 5000\}$
Gradient boosting with regression trees	$\eta \in \{0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5\}$	$T \in \{1, 200, 600, 1000, 2000, 6000, 8000\}$
Feed-forward neural networks	$H \in \{1, 2, 3, 4, 5, 6\}$	$N \in \{32, 64, 128, 256, 512\}$

Table 7: Tuning parameters selected based on the considered sets of variables.

Methods	Pairs of parameters	Variables sets			
		PF	RO	RO PF	RO PF+M
Random forests	$(T, m) =$	(10, 15)	(100, 10)	(500, 5)	(5000, 7)
Gradient boosting with regression trees	$(T, \eta) =$	(6000, 0.0005)	(8000, 0.0005)	(6000, 0.005)	(6000, 0.005)
Feed-forward neural networks	$(N, H) =$	(256, 5)	(32, 4)	(32, 4)	(64, 2)

The final function  $f$  is obtained by fitting  $\theta$  on data:

$$f = f_{\hat{\theta}}, \quad \text{where} \quad \hat{\theta} \in \underset{\theta}{\operatorname{argmin}} \sum_{k,s,d} (y_{k,s,d}^{\text{obs}} - f_{\theta}(\mathbf{X}_{k,s,d}))^2.$$

Efficient gradient-descent techniques (the so-called gradient back-propagation algorithm) exist to perform the optimization leading to the value of  $\hat{\theta}$  (which is called “training the network”). We use the R package `keras` to build the architecture and the R package `tensorflow` to train the network. The model is trained with batch size 32 and mean absolute error as the loss function (see Section 3.6). We use the classical `Adam` optimizer, which is based on stochastic sampling, to compute gradients. We run 50 epochs, not more (to avoid over-fitting), not fewer (to train sufficiently the parameters).

### 3.6. Fair assessment of the performance: picking parameters on a train set, and evaluating performance on a test set

All methods above require some training on historical data. Fitting the coefficients of the linear regression models on such historical data is straightforward. Machine-learning techniques (random forests, gradient boosting with regression trees, and feed-forward neural networks) require a more sophisticated use of historical data: they need to pick some hyperparameters—two per method, which we recall in Table 6—and fit the model on data based on these hyperparameters.

A popular solution in statistics, already considered in transportation research by, among others, Kecman and Goverde [2015], consists in separating the data set into two subsets: a train data set and a test data set. The train data set is used both to select hyperparameters and fit the models accordingly, by cross-validation (see Section A.2 in appendix). The test data set is used to evaluate the performance of the thus constructed methods. Doing so, we avoid favorable biases that would consist, for instance, of constructing and evaluating the methods on the same data subset; in that case, we would be providing some in-sample error rather than an out-of-sample error. More precisely, we consider a fixed 60%–40% breakdown of the data set into a train data set (data points from March

15, 2018 to March 15, 2019) and a test data set (data points from March 16, 2019 to September 15, 2019).

Hyperparameters are selected based on grids of possible values, provided in Table 6. These grids had been determined *ex ante* and were constructed based on previous choices of these hyperparameters in the literature. For random forests, we built the grids around the default parameters of the `ranger` package (see Wright and Ziegler, 2017), which equal  $m = \lfloor \sqrt{p} \rfloor$  for `mtry` (where  $p$  is the number of input variables considered) and  $T = 500$  for `ntree`; given the values of  $p$  (see Table 4), this leads to  $m = 4$  or  $m = 5$ . For gradient boosting with regression trees, we take the exact same grids as considered by Zhang and Haghani [2015, Section 3.2]. For the feed-forward neural networks, we built a reasonable grid based on the default values  $N = 256$  units and  $H = 2$  hidden layers chosen by Li et al. [2018, Annex E].

**Outcome.** It turns out that the performance of the machine learning methods is not too sensitive to the pairs of hyperparameters considered: Section A.1 in appendix tabulates the performance of the methods on the grids of Table 6 and we observe therein that whenever these hyperparameters are large enough, a close-to-optimal performance is reached.

Despite all, we alleviate the burden of users by providing in Section A.2 a fully automated procedure to select these parameters on the train data set. This procedure consists of two passes on the train data set, a first to select the hyperparameters, based on cross validation, and a second to fit the corresponding model. The outcome is reported in Table 7. These are the hyperparameters we use in the rest of the article.

## 4. Main Results

The previous section described machine-learning methods to build single data-driven models for dwell time valid for all stations, all working days, all hours, and all trains. In this section, we quantify their modeling performance, i.e., report the modeling errors described in Section 4.1, namely, the mean absolute modeling errors and the root mean squared modeling errors. We do so both at a global level (Section 4.2) and at a local level (Section 4.3), possibly also by considering an addition breakdown of the modeling performance by regimes of punctuality or affluence (Section 4.4). By “global” results, we mean errors obtained by global averages over all stations, all working days, all hours, and all trains. By “local” results, we mean conditional averages of the form “average error suffered when some explanatory variable equals a given value”. We of course define first more formally the concept of “local” performance Section 4.3. We conclude by a ranking of the explanatory variables depending on their modeling influence (Section 4.5).

### 4.1. Metrics for the assessment of performance

With the notation of Section 3, models  $\hat{f}$  are built on the train set and are evaluated on the test set  $\mathcal{T}_{\text{est}}$ , whose cardinality is denoted by  $N_{\mathcal{T}_{\text{est}}}$ . The mean absolute error (MAE) and root mean squared error (RMSE) of such a model  $\hat{f}$  are respectively defined by

$$\text{MAE}(\hat{f}) = \frac{1}{N_{\mathcal{T}_{\text{est}}}} \sum_{(k,s,d) \in \mathcal{T}_{\text{est}}} \left| y_{k,s,d}^{\text{obs}} - \hat{f}(\mathbf{X}_{k,s,d}) \right|$$

and

$$\text{RMSE}(\hat{f}) = \sqrt{\frac{1}{N_{\mathcal{T}_{\text{est}}}} \sum_{(k,s,d) \in \mathcal{T}_{\text{est}}} \left( y_{k,s,d}^{\text{obs}} - \hat{f}(\mathbf{X}_{k,s,d}) \right)^2}.$$

No metric seems preferred in the transportation literature, and each has its own advantages: MAE summarizes best the global performance while RMSE is sensitive to large errors.

Table 8: Modeling performance for each method and each set of variables, in MAE (*left part of the table*) and RMSE (*right part of the table*). Columns indicate which variables are used (see Section 3.1): only passenger flows [PF] variables, only railway operations [RO] variables, both RO and PF variables, and all variables (RO, PF, and M, the affluence at the critical door). Each line corresponds to a method to process data: linear regressions (Section 3.3), random forests and gradient boosting (Section 3.4), feed-forward neural networks (Section 3.5). Standard errors are smaller than 0.03 seconds.

Methods	MAE				RMSE			
	PF	RO	RO PF	RO PF+M	PF	RO	RO PF	RO PF+M
1. Linear regression with additive effects	13.7	10.5	10.2	10.1	18.4	14.8	14.5	14.3
2. Linear regression with a multiplicative effect of $\Delta a$ by $z$	13.7	9.1	8.9	8.8	18.4	13.6	13.2	13.1
3. Linear regression with multiplicative effects by triplets $(s, w, z)$	13.3	8.8	8.3	8.3	18.0	13.2	12.6	12.5
4. Random forests	13.7	8.4	8.1	8.0	18.8	12.9	12.5	12.3
5. Gradient boosting with regression trees	12.9	8.5	8.0	7.9	17.9	13.0	12.4	12.2
6. Feed-forward neural networks	12.7	8.4	8.0	8.0	17.4	13.0	12.4	12.2

## 4.2. Main table: global performance

Table 8 reports the global performance for the modeling of dwell time, i.e., the MAE and the RMSE achieved on the entire test data set, of the six methods presented in Sections 3.3–3.5 run on four possible subsets of variables described in Section 3.1.

We first comment how the modeling performance depends on the subsets of variables. Using passenger flows [PF] variables only is suboptimal, and railway operations [RO] variables seem key to achieve the best performance. We also observe that overall, using RO variables only is not as good as using RO and PF variables simultaneously, which is itself slightly outperformed by using RO and PF variables together with the M variable consisting of the affluence at the critical door. The observations made above are consistent with previous observations in the literature, which deemed RO variables more important than PF variables for commuter trains (Hansen et al., 2010, Kecman and Goverde, 2015). We detail in subsequent subsections how PF variables, including the M variable, are valuable to consider on top of RO variables. This will, in particular, show the genuine interest of the PF and M variables, which, for now, seems modest on Table 8—while one could have expected a more dramatic effect based on the study by Wirasinghe and Szplett [1984].

We now comment the influence of the method. We first observe that the more complex the linear regression models, the better the performance. But linear regression models, which provide explainable relationships, exhibit suboptimal performance compared to the machine-learning methods (random forests, gradient boosting with regression trees, feed-forward neural networks), which do not offer explicit relationships and only provide black-box (highly non-linear) modelings. Among these machine-learning methods, gradient boosting with regression trees performs slightly better than random forests and feed-forward neural networks. All in all, the linear regression with a multiplicative effect of  $\Delta a$  by  $z$  probably offers the best trade-off, among all six methods considered, between simplicity, explainability and performance.

### 4.3. “Local” performance, depending on the level of explanatory variables

We now provide a more “local” study of performance: instead of reporting global measures of performance, we rather explain how performance varies as a given explanatory variable (affluence, deviation to scheduled arrival time, etc.) varies. For the sake of concision, we will only consider one machine-learning method; to allow comparison to earlier results, we select random forests: Kecman and Goverde [2015] ran random forests on RO variables, and we will be running them also on all variables (RO, PF, and M). We will refer to both instances of random forests by the short-hand notation RF–RO and RF–All.

Our main aim in this section is to highlight the added value of considering PF and M variables on top of RO variables: while the fourth line of Table 8 shows an extremely similar global performance of RF–RO and RF–All, we will demonstrate improvements in the “local” performance thereof. We first explain how we define and compute the latter.

**Concept of local performance.** We merely describe here how Figures 6–9 were obtained and how they measure local performance. We comment below on the gain in efficiency brought by RF–All with respect to RF–RO, in a dedicated series of paragraph.

Figures 6–9 aim to illustrate the impact of affluence  $A + B$  (the sum of the numbers of passengers alighting plus the ones boarding), which is to be found in  $x$ -axis, on performance for the modeling of dwell time, which is to be found in  $y$ -axis. This performance may be measured in an absolute manner (for RF–RO or for RF–All, as in the left graph of Figure 7) or in a relative manner (improvement of RF–All over RF–RO, as in the right graph of Figure 7).

We explain first how local performance is measured in an absolute manner. We fix a given method, say, RF–All. The scatterplot underlying the left graph of Figure 6 consists of the pairs

$$\left( A_{k,s,d} + B_{k,s,d}, \left| y_{k,s,d}^{\text{obs}} - \hat{f}(\mathbf{X}_{k,s,d}) \right| \right)$$

as  $(k, s, d)$  varies in the test set  $\mathcal{T}$ est. We apply the same smoothing as in Figure 3. Doing so, we obtain a curve representing the average absolute error in the modeling of dwell time by the level of affluence (solid line); this average is associated with a  $\pm 2$  times standard deviation (dotted lines). The right graph of Figure 6 is simply a cleaned version of the left one, where we erased the underlying scatterplot.

Now, the representation just described may be performed for RF–RO and for RF–All: see the left graph of Figure 7, where we also added a  $\pm 1$  s tube starting from the dotted lines. This tube measures the significant improvements: as dwell time is measured with 2 s steps (see Table 2), we are only interested in average improvements larger than 1 s. We may read on the left graph the range where RF–All improves significantly over RF–All: the range where the lower part of the tube around RF–RO is higher than the upper dotted line for RF–All. This range accounts for 5.8% of the observations, as we write on the blue arrow under the curves.

We represent this comparison in an equivalent manner on the right graph of Figure 7: the average difference by affluence is the difference of the average absolute errors by affluence between RF–RO and

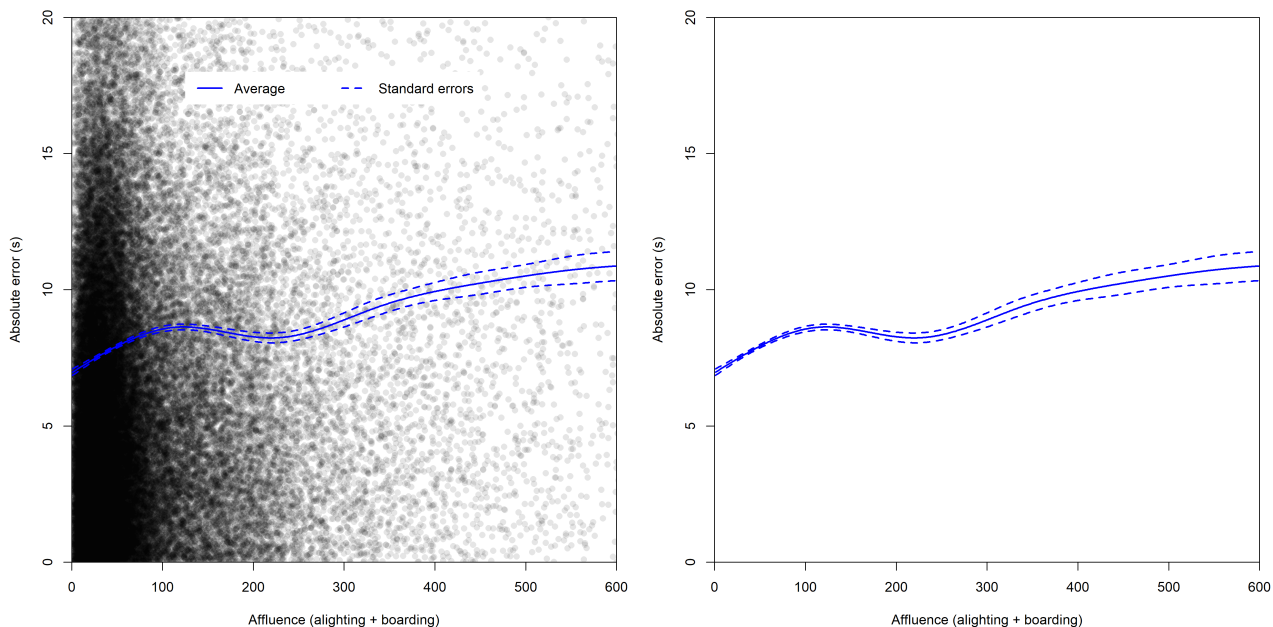


Figure 6: Left graph: scatterplot of the absolute errors on the test set for dwell time modeling by RF-All plotted against affluence, together with an estimation of the associated average absolute errors (solid line), and standard errors thereof (dotted lines). Right graph: left graph without the underlying scatterplot.

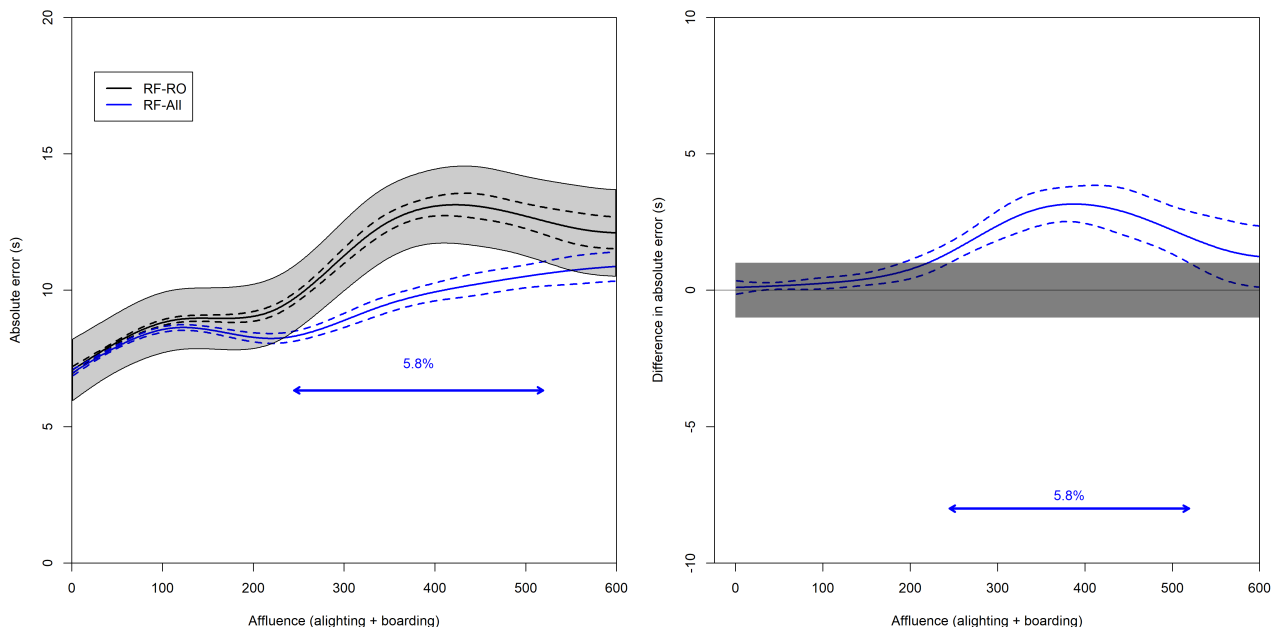


Figure 7: Left graph: average absolute error for the modeling of dwell time ( $y$ -axis) by affluence ( $x$ -axis) for RF-RO (black) and RF-All (blue). Right graph: difference of these average absolute errors, between RF-RO and RF-All.

RF–All, and the associated standard deviations are the sums of the standard deviations associated with the average errors of RF–RO and RF–All. The same  $\pm 1$  s tube is depicted, around the value 0.

We may proceed similarly with square errors for the modeling of dwell time. The left graph of Figure 8 depicts the scatterplot of

$$\left( A_{k,s,d} + B_{k,s,d}, \left( y_{k,s,d}^{\text{obs}} - \hat{f}(\mathbf{X}_{k,s,d}) \right)^2 \right)$$

as  $(k, s, d)$  varies in the test set  $\mathcal{T}_{\text{test}}$ . Average squared errors by affluence and their associated  $\pm 2$  standard deviations may then be computed, exactly as in the left graph of Figure 6. The right graph of Figure 6 depicts the roots of the curves computed in Figure 6, and they correspond to root mean square errors by the affluence, associated with measures of deviations. The left graph of Figure 9 provides such curves for RF–RO (together with a  $\pm 1$  s tube) and RF–All, while the right graph of Figure 9 is the difference between these curves, in the RF–RO minus RF–All direction.

**Comments on local performance by affluence (Figures 6–9).** These figures generally show that the improvement in the dwell time modeling from RF–RO to RF–All, i.e., when taking PF and M variables into account, lies in situations with a high affluence. These account for a limited share of the situations considered: around 5 to 7% of them. Yet, these are exactly the situations where the modeling of dwell time is challenging, as can be seen from the relatively large average errors made by the reference model RF–RO. In particular, the left graph of Figure 9 shows that RF–All enjoys a more steady performance, while the one of RF–RO worsens as affluence increases.

**Comments on local performance by observed dwell time (Figure 10).** Figure 10 depicts how modeling errors vary with the observed dwell time  $y^{\text{obs}}$ . Errors for both RF–RO and RF–All methods follow U-shaped curves, with a low plateau in the 40 s – 90 s range, and with linear increases outside of this range. The RF–All method outperforms significantly the RF–RO method on average for extreme values of the observed dwell time: short dwell times (inferior to 22 s) and long dwell times (larger than 110 s). These values only account for 3 to 5% of all observations. No scheduled dwell time is shorter than 30 s, so, observed dwell times shorter than 22 s must correspond to trains with a delay and low affluence, that attempt to leave the station as early as possible. This hints at the necessity of a study of local performance by deviation to scheduled arrival time, which we provide next. We have no convincing or consistent explanations for the improvements for longer dwell times.

**Comments on local performance by deviation to scheduled arrival time (Figure 11).** Figure 11 depicts how modeling errors vary with the deviation  $\Delta a$  to scheduled arrival time. As for Figure 10, errors for both RF–RO and RF–All methods follow U-shaped curves with a minimum reached at  $\Delta a = 0$ , i.e., when trains are perfectly on time. On the first part of the U-shaped curves, i.e., for early trains, the performance of RF–RO and RF–All exhibit is virtually indistinguishable. This is certainly explained by the fact that early trains wait longer than needed in a station; therefore, passenger flows do not constrain dwell times. On the contrary, on the second part of the U-shaped curves, i.e., for late trains, RF–All consistently outperforms RF–RO, in a statistically significant manner as soon as  $\Delta a$  is larger than something of the order of 70 s, which accounts for 14% of the total observations in MAE (and 7% in RMSE). The rough improvement in performance lies is of order 2 – 3 s, for errors of the order of 10 – 15 s. These observations thus show that for delayed trains, passenger flows are a key determinant of dwell time, as intuition commands: trains attempt to leave a station as fast as possible when they are late on schedule.

#### 4.4. Breakdown of the performance by regimes of punctuality or affluence

The local performance study above highlights the situations where taking passenger flows into consideration helps (i.e., where RF–All is superior to RF–RO): in case of large delays to scheduled arrival

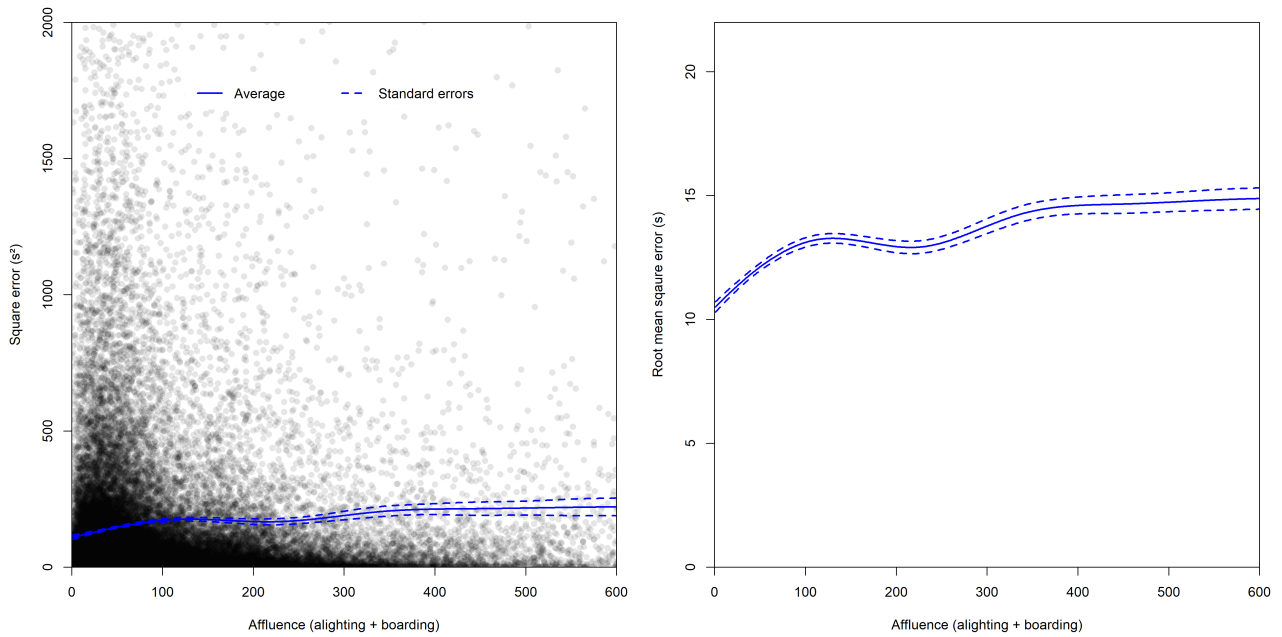


Figure 8: Left graph: scatterplot of the squared errors on the test set for dwell time modeling by RF-All plotted against affluence, together with an estimation of the associated average squared errors (solid line), and standard errors thereof (dotted lines). Right graph: root of the curves obtained in the left graph, corresponding to root mean square errors by affluence.

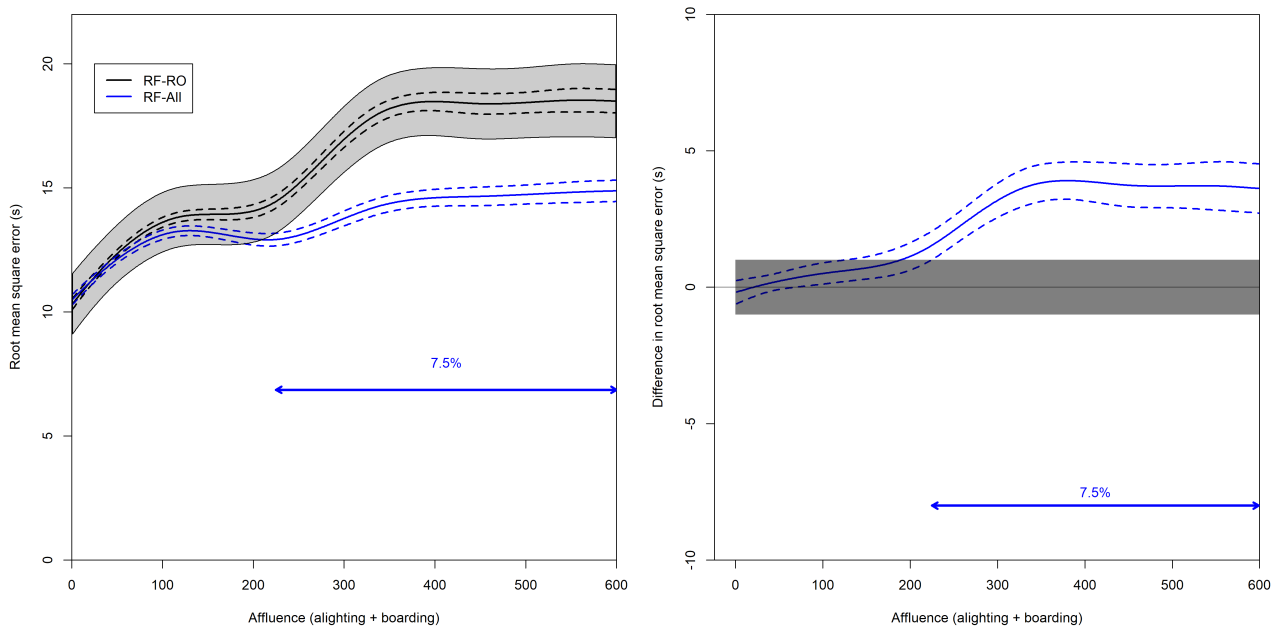


Figure 9: Left graph: root mean square errors for the modeling of dwell time ( $y$ -axis) by affluence ( $x$ -axis) for RF-RO (black) and RF-All (blue). Right graph: difference of these root mean square errors, between RF-RO and RF-All.



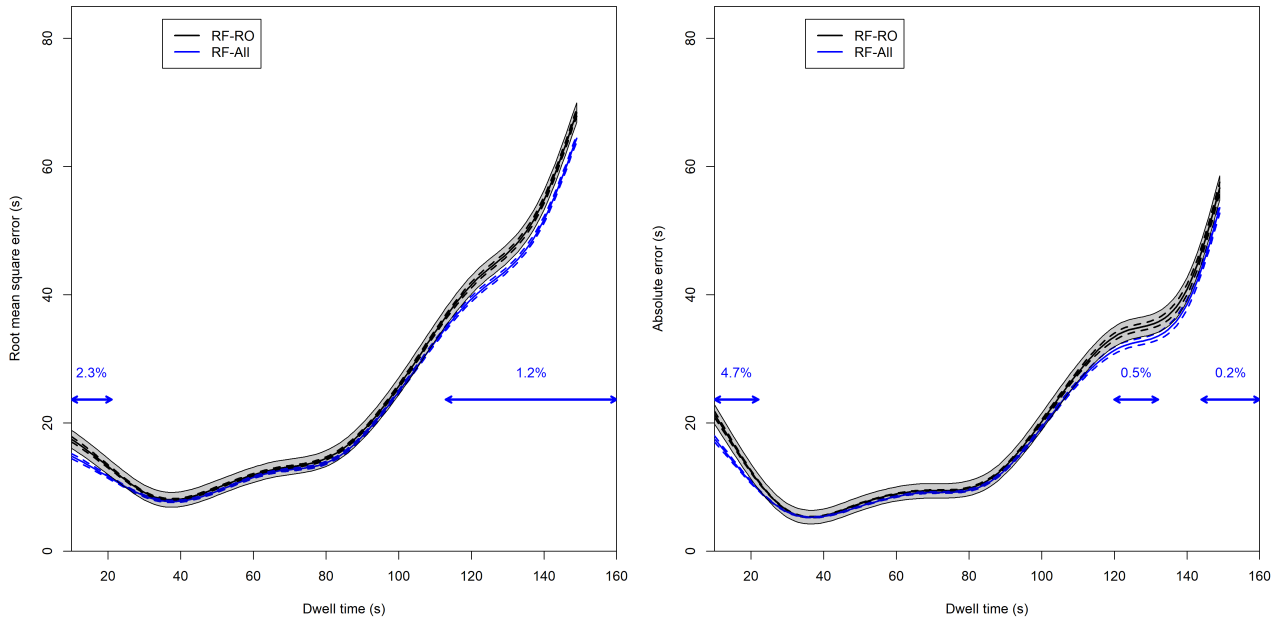


Figure 10: Root mean square errors (left graph) and absolute errors (right graph) for the modeling of dwell time ( $y$ -axis) by observed dwell time ( $x$ -axis) for RF-RO (black) and RF-All (blue).

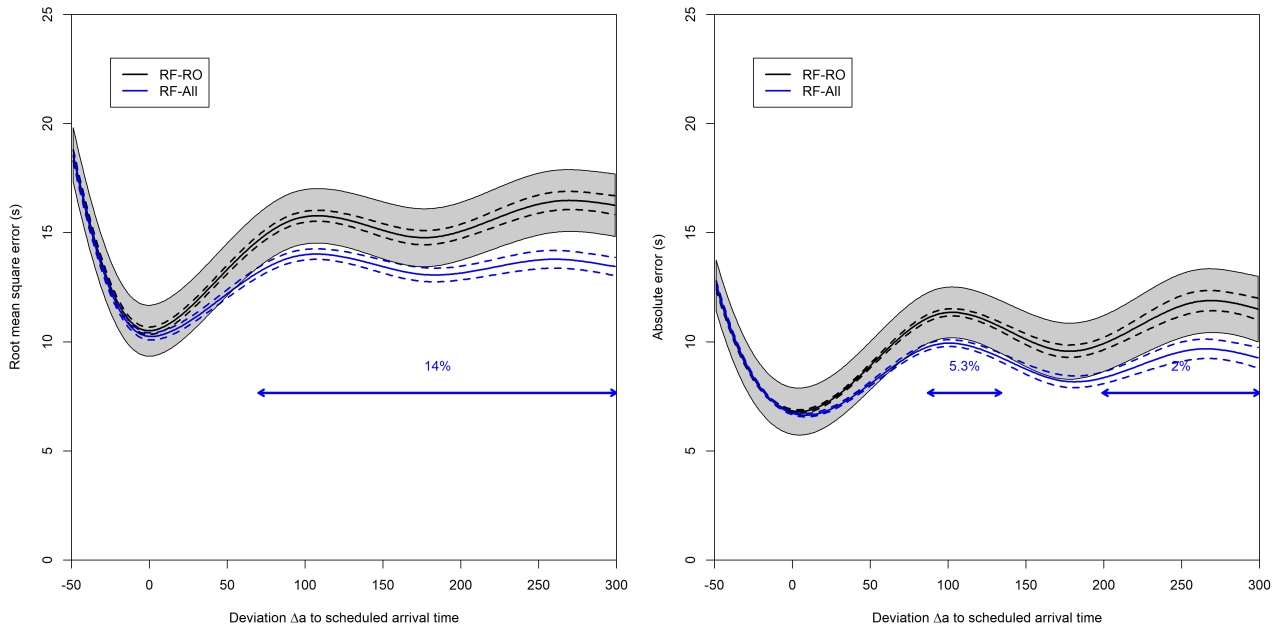


Figure 11: Root mean square errors (left graph) and absolute errors (right graph) for the modeling of dwell time ( $y$ -axis) by deviation  $\Delta a$  to scheduled arrival time ( $x$ -axis) for RF-RO (black) and RF-All (blue).

Table 9: Breakdown of the data set for line L by regimes of punctuality or affluence.

Punctuality	Early: 54,697	On time: 34,388	Late: 28,242
Affluence	Low: 58,813	High: 58,514	

time or high affluence. We now clarify further these determinants by looking at their joint influence: we break down the performance by regimes of punctuality or affluence.

The regimes of punctuality considered were already explained in Table 3: trains may be early, on time, or late. We define two regimes of affluence, high and low, setting as threshold a quasi-median of the affluences  $A_{k,s,d} + B_{k,s,d}$  observed on the test data set: we use 51–52 as thresholds (low affluence is affluence  $\leq 51$  and high affluence is affluence  $\geq 52$ ). All in all, the 117,327 triplets  $(k, s, d)$  of the test data set may be broken down as indicated in Table 9.

In this section, we follow somewhat the structure of the previous analysis and first report global numerical results factored by regimes of punctuality or regimes of affluence (a table), and second, provide a more local, graphical, idea of the improvement in performance of RF–All over RF–RO factored by regimes of punctuality or affluence. Finally, we analyse the importance of variables by regimes of punctuality, i.e., pin point the variables that are the most important to model dwell time for each regime of punctuality.

**Global performance by regimes of punctuality or regimes of affluence.** Table 10 deepens the results of the fourth line of Table 8, which was devoted to random forests: the first line of Table 10 is a mere copy of the fourth line of Table 8. We then break down the performance achieved on the test data set by regimes of punctuality, i.e., compute the errors only over early trains, trains on time, or late trains. The first line of Table 10 is therefore a weighted average of its second, third, and fourth lines.

We first comment the influence of the regime of punctuality on performance. The smallest errors are always observed for trains on time, then for early trains, while the largest errors are suffered for late trains. The influence of the subsets of variables considered is similar to what was observed already in Table 8: RO variables in isolation are more useful than PF variables in isolation, while the simultaneous consideration of RO and PF variables is even better, with the consideration of the critical door data (subset M) not changing substantially performance.

For regimes of affluence, similar observations may be issued concerning the subsets of variables, noting however that the added value of PF variables on top of RO variables is larger in the case of a high affluence than for a low affluence. Generally speaking, dwell time is more difficult to predict in situations of high affluence, as intuition commands.

**Local performance by affluence factored by regimes of punctuality (Figure 12).** On Figure 12, we break down by regimes of punctuality the differences in modeling errors between RF–RO and RF–ALL as functions of the affluence already depicted in the right graphs of Figure 7 and 9. Therein, we had noticed a significant reduction of the errors in 5% to 7.5% of the cases. We observe that these cases correspond to late trains and trains on time, but to no early train. Also, the obtained improvements are larger for late trains than for trains on time and/or take place for lower values of affluence.

**Local performance by dwell time factored by regimes of punctuality (Figure 13).** Figure 13 is the counterpart of Figure 10, where we broke down the differences in modeling errors as functions of the observed dwell times by regimes of punctuality. In this case as well, RF–RO and RF–All obtain the same performance on early trains (which are the only ones with observed dwell times

Table 10: Modeling performance for random forests by regimes of punctuality or regimes of affluence (lines) and for each subset of variables (rows); see the legend of Table 8), in MAE (*left part of the table*) and RMSE (*right part of the table*). Standard errors are smaller than 0.03 seconds.

Random forests	MAE				RMSE			
	PF	RO	RO PF	RO PF+M	PF	RO	RO PF	RO PF+M
All trains	13.7	8.4	8.1	8.0	18.8	12.9	12.5	12.3
Early trains	15.4	7.9	8.0	7.9	21.0	12.5	12.6	12.4
Trains on time	11.8	8.3	7.8	7.8	16.2	12.4	11.9	11.7
Late trains	12.7	9.7	8.5	8.5	17.2	14.2	12.9	12.7
Low affluence	12.4	7.6	7.5	7.5	16.9	11.4	11.3	11.4
High affluence	15.0	9.2	8.7	8.5	20.5	14.3	13.5	13.1

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larger than 100 s). Improvements in performance are mostly due to late trains, for which between 20% and 30% of the data points are better modeled; improvements due to trains on time are negligible. These improvements take place, as in Figure 10, in a U-shaped fashion, for small and large values of the observed dwell times.

**Local performance by dwell time factored by affluence regime (Figure 14).** In Figure 14 we represent the differences in modeling errors between RF-RO and RF-ALL as functions of the dwell time, with a break down by regimes of affluence. As in Figures 10 and 13 we observe improvements of RF-All over RF-RO for short (inferior to 20 s) or long (larger than 90 s) dwell times. But interestingly, there is a clear association of regimes: improvements for short dwell times only take place in the case of low affluence, while improvements for long dwell times happen only in the case of high affluence.

**Local performance by deviation to scheduled arrival time factored by affluence regime (Figure 15).** We represent in Figure 15 the differences in modeling errors between RF-RO and RF-ALL as a function of the deviation  $\Delta a$  to scheduled arrival time and break it down by regimes of affluence. This figure is the counterpart of Figure 11, where we observed modest improvements of RF-All over RF-RO for deviations larger than something of the order of 50 s. Figure 15 shows that these modest improvements are all associated with high affluence.

#### 4.5. Most influential variables

We recall a general methodology to determine which variables are the most influential in a random-forest modeling, explain how we implemented it on our data set, and discuss the obtained results, with a special focus on the identification of the most influential variables by regimes of punctuality.

**General methodology.** Two main family of methododologies exist to determine which explanatory variables are the most influential for random forests on a given data set: mean decrease accuracy [MDA]

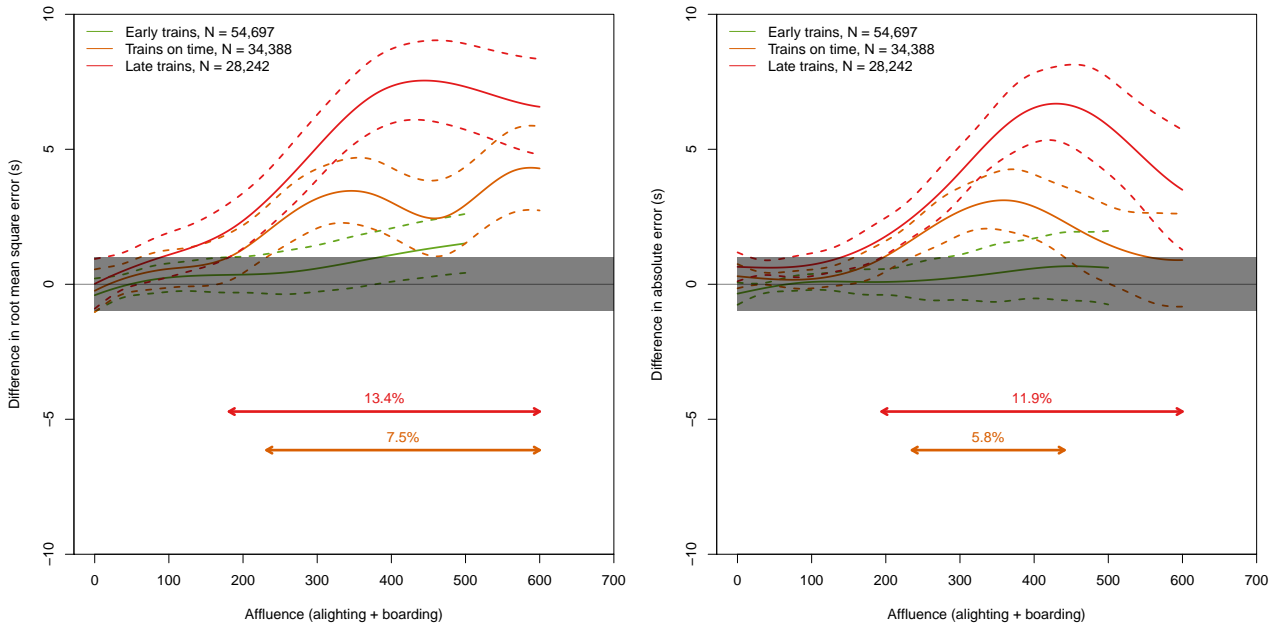


Figure 12: Differences in mean square errors (left graph) and absolute errors (right graph) between RF-RO and RF-All for the modeling of dwell time ( $y$ -axis) by affluence ( $x$ -axis), factored by regimes of punctuality. Positive numbers correspond to the superiority of RF-All over RF-RO.

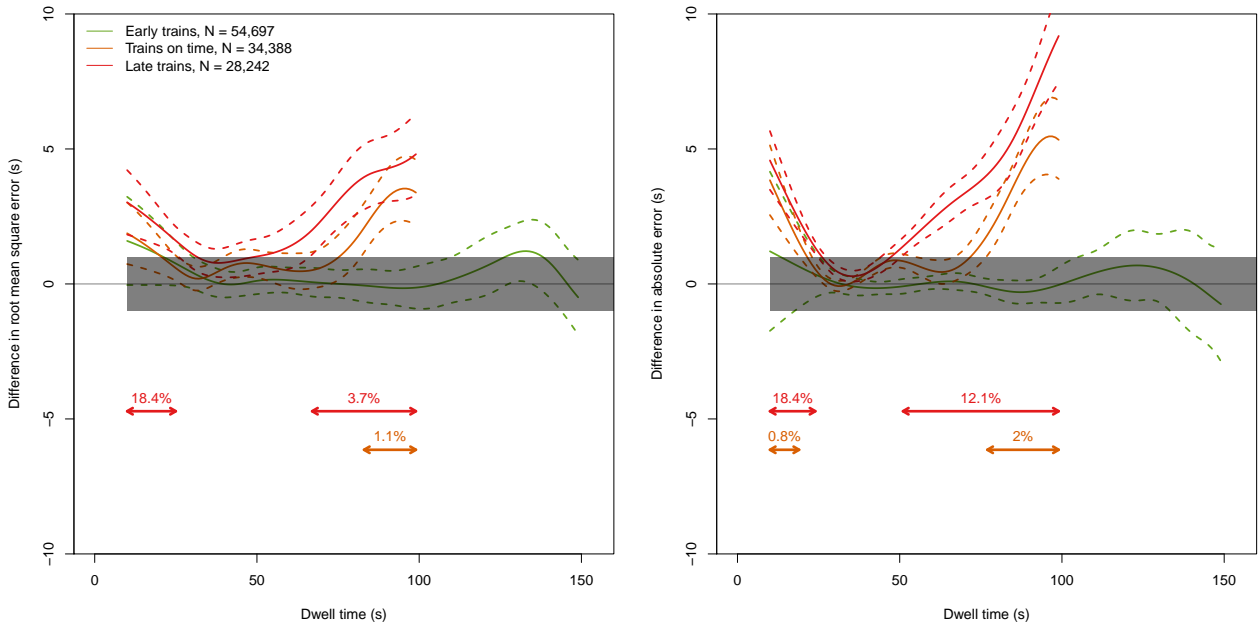


Figure 13: Differences in mean square errors (left graph) and absolute errors (right graph) between RF-RO and RF-All for the modeling of dwell time ( $y$ -axis) by observed dwell time ( $x$ -axis), factored by regimes of punctuality. Positive numbers correspond to the superiority of RF-All over RF-RO.

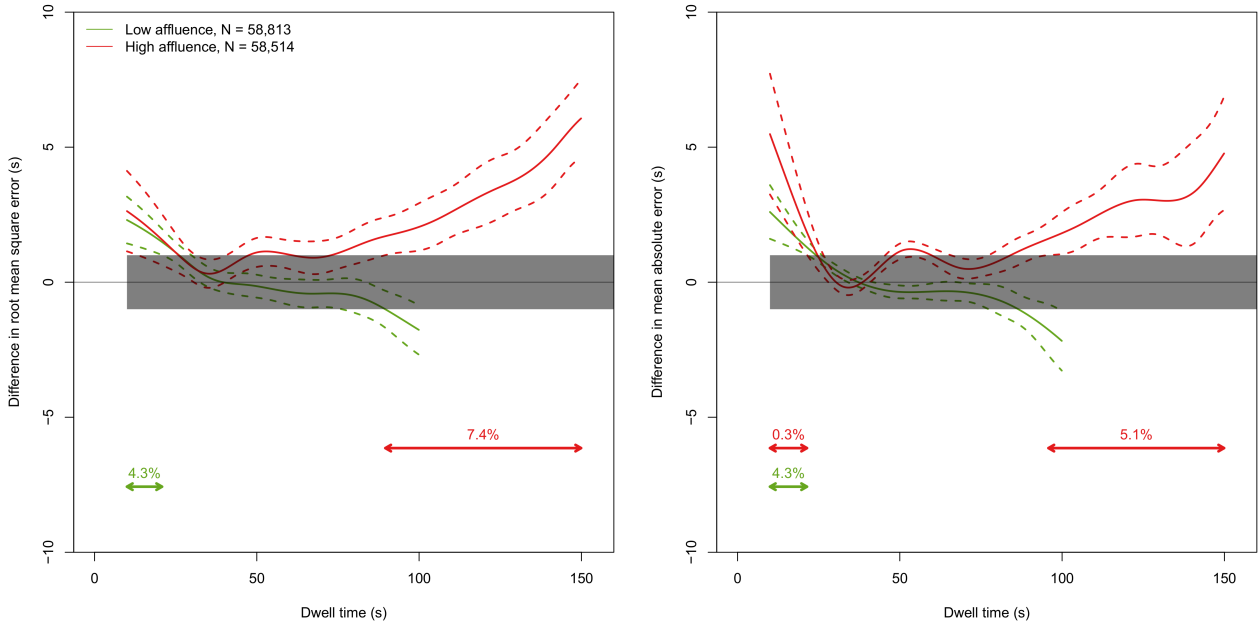


Figure 14: Differences in mean square errors (left graph) and absolute errors (right graph) for the modeling of dwell time ( $y$ -axis) by observed dwell time ( $x$ -axis), factored by affluence regime. Positive numbers correspond to the superiority of RF-All over RF-RO.

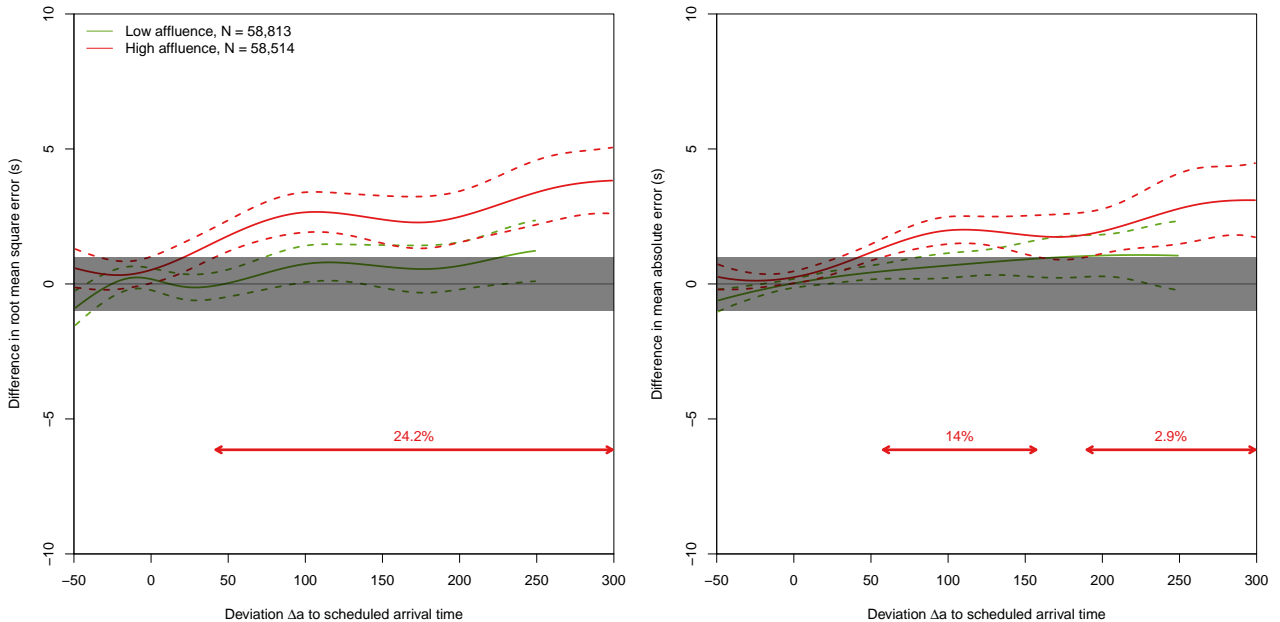


Figure 15: Differences in mean square errors (left graph) and absolute errors (right graph) for the modeling of dwell time ( $y$ -axis) by deviation  $\Delta a$  to scheduled arrival time ( $x$ -axis), factored by affluence regime. Positive numbers correspond to the superiority of RF-All over RF-RO.

and mean decrease impurity [MDI]. Each of them may be implemented in several specific ways despite a common spirit for each methodology proposed by Breiman [2001]. We discuss below the specific implementations provided by the R package `ranger` already mentioned in Section 3.4 (see Wright and Ziegler, 2017), corresponding to the options `permutation` [MDA] and `impurity` [MDI]. The most popular criterion is probably MDA but we provide here the results obtained for both criteria.

We recall that random forests exploit instances  $\mathbf{X}_{k,s,d}$  of vectors of variables  $\mathbf{X} = (X_1, \dots, X_p)$ .

The spirit of MDA is the following: for each variable  $j$ , an index  $\text{MDA}_j$  is computed as follows. We first bootstrap data with replacement into  $T$  data sets (where  $T$  is the number of trees of Table 7) compute a random forest based on each of these  $T$  bootstrapped data sets, and evaluate an average difference of performance on the remainder observations of each of these data sets (the so-called out-of-bag observations): the average squared error on modified out-of-bag observations, obtained by randomly permuting the values of the variable of interest, minus the average squared error on original out-of-bag observations. The larger this average difference  $\text{MDA}_j$ , the more crucial the variable under scrutiny.

As explained in Section 3.4, each tree  $f^{(t)}$  of a forest is grown through refinements decided based on maximal reductions of in-sample errors, and MDI exploits this construction:  $\text{MDI}_j^{(t)}$  is simply the weighted sum of the reductions associated with the same variable  $j$ , over all refinements leading to tree  $f^{(t)}$ , where the weights are the proportion of observations falling in the region to be refined. The final index  $\text{MDI}_j$  is then obtained by averaging out the  $\text{MDI}_j^{(t)}$  over the  $T$  trees of the forest.

In both cases, we obtain non-negative families of indices  $(\text{MDA}_j)_{1 \leq j \leq p}$  and  $(\text{MDI}_j)_{1 \leq j \leq p}$  and we depict on Figure 16 the normalized vectors

$$\frac{\text{MDA}_j}{\sum_{i=1}^p \text{MDA}_i} \quad \text{and} \quad \frac{\text{MDI}_j}{\sum_{i=1}^p \text{MDI}_i}, \quad \text{where } j = 1, \dots, p.$$

**Specific application.** The first line of Figure 16 provides the normalized MDA and MDI indices for RF–All run on the entire data set; the 21 variables it relies on (see last column of Table 5) are ranked according to their normalized indices.

We also run RF–All (still tuned with the hyperparameters of the last column of Table 7) on each of the three subsets defined by regimes of punctuality; when we do so, we only feed RF–All with 18 variables, omitting the three binary categorical variables stemming from the regime of punctuality  $z$  (given that they would be constant anyway on each of the subsets). The bottom three lines of Figure 16 provide the normalized MDA and MDI indices computed for each regime of punctuality.

**Results.** Be it for MDA or MDI indices, the top three influential variables are, globally, the scheduled dwell time  $y^{\text{theo}}$ , the affluence at the critical door  $M$ , and the deviation to scheduled arrival time  $\Delta a$ . Then come the numbers  $A$  and  $B$  of alighting and boarding passengers, as well as the crowding factor  $C$  and the fact that the train is early, i.e.,  $z = 1$ .

This picture is somewhat similar for early trains. For trains on time and late train, the MDA procedure rather points to the critical affluence  $M$  as the main driving factor, with alighting number  $A$  and scheduled dwell time  $y^{\text{theo}}$  as the next most important variables.

In all cases, stations are among the least influential variables, except maybe for La Défense and Saint-Cloud.

## 5. Conclusions and research perspectives

**Conclusions.** This article considers a particularly rich data set containing both railway operations variables and door-by-door passenger flows variables. We considered the modeling of the observed dwell time based on these two subsets of variables and proved that while railway operations variables

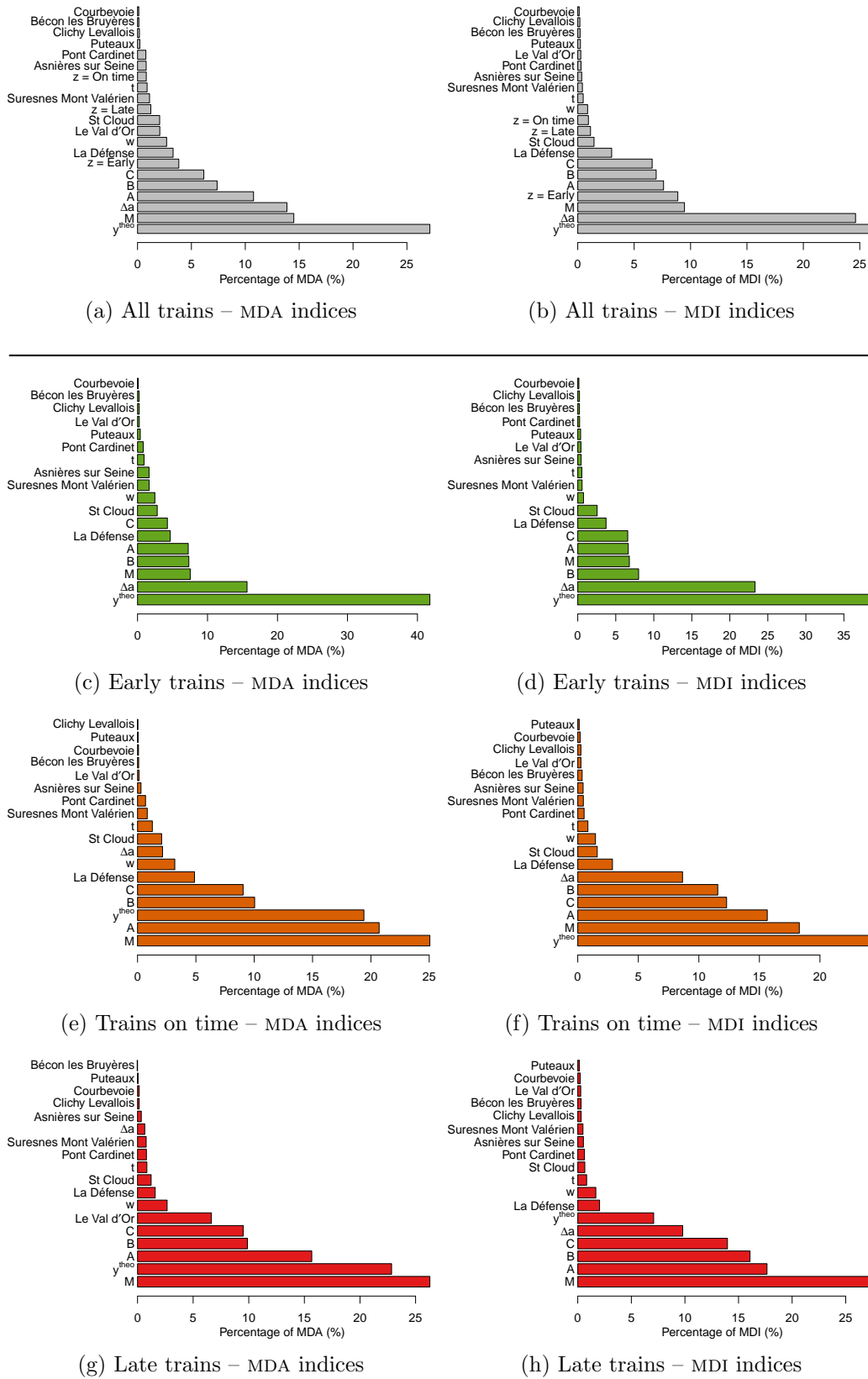


Figure 16: The most influential variables using normalized MDA indices (left) and normalized MDI indices (right) for RF–All on the entire data set (first line) or RF–All run on sub-data sets corresponding to the regimes of punctuality (last three lines).

are key for low modeling errors, passenger flows variables provide an added value both at the global level (average reduction of the global modeling error by about 0.5 s) and at the local level (average reductions of the modeling errors up to 5 – 10 s in challenging situations consisting, e.g., of late trains or associated with high affluence). Railway operations variables are the most influential variables for early trains (which are constrained by the scheduled departure time and must wait for possibly an extended amount of time) while passenger flows variables are the most influential variables for late trains (which leave the station right after the passenger exchange time), and also, for trains on time. These phenomena were expected, of course, but are confirmed on data.

Method-wise, we discussed fully automated model-building techniques (in particular, thanks to setting their hyperparameters on data). Among them, we favored random forests but note that a well-suited formulation of linear regression with multiplicative effects obtains a comparable, though slightly worse, performance.

**Research perspectives.** The main perspective is to now provide forecasts of the dwell time. The models studied in this article rely on information (passenger exchange numbers, deviation to scheduled arrival time) that are unknown in advance but could be predicted, possibly in simple ways: the deviation to the scheduled arrival time expected at future stations equals the deviation to the scheduled departure time suffered at the present station, for instance, while passenger exchange numbers could be predicted by some average values. Doing so, and using one of the models built on historical data, we would obtain real-time predictions of the dwell time at future stations, that would get updated each time the considered train leaves a station.

Other research perspectives lies in drawing conclusions on the models built in terms of designs: design of the timetables or design of the platforms of the stations. More precisely, the model could be fed with observed (joint) distributions of deviations to scheduled arrival time and passenger flows to simulate distributions of dwell times and better design the timetables through setting a careful but possibly shorter buffer time (see Figure 1), or studying the effect of adding trains during peak hours. Also, the role and importance of the critical door on dwell time could be better understood, so as to draw conclusions in terms of physical design of the platforms, if needed.

All in all, we provided methods to output modelings of the dwell time, but these models should be extended to predictive models, or should be used for simulation and design purposes.



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## A. Details on hyperparameters (a.k.a. tuning parameters) of machine-learning methods

Section 3.6 briefly explains that machine-learning methods need to pick some hyperparameters on the train data set—two per method, which we indicated in Table 6—and fit a model on the same train data set based on these hyperparameters.

In this appendix, we first illustrate through a sensitivity analysis (Section A.1) that the selection of these hyperparameters is not crucial; we then nonetheless describe in detail the cross-validation methodology we used to perform this selection (Section A.2).

### A.1. Sensitivity analysis

We illustrate in Figures 17–19 how tuning parameters affect performance, both in RMSE and MAE, when taking all variables (RO, PF and M ones) into account; similar conclusions are reached for subsets of variables. On this figures, we report the performance obtained on the test data set by fitting models on the train data set based on each pair of tuning parameters of Table 6. The overall conclusion is that many pairs of tuning parameters lead to an approximately equal performance, and that these pairs consist of large enough parameters, while some parameters that are too small may lead to suboptimal performance. We conclude that the selection of tuning parameters is not a crucial issue.

More precisely, the sensitivity of random forests is illustrated in Figure 17; for clarity, we represent only a part of all possible pairs  $(m, T)$  of tuning parameters. Pairs with numbers of variables  $m \geq 6$  and numbers of trees  $T \geq 50$  obtain basically the same performance. The stability of performance is even more remarkable for feed-forward neural networks, as can be seen on Figure 19: all pairs exhibit a performance that lies in a range of radius of order  $\pm 0.5s$ . There is slightly more instability for gradient boosting with regression trees, even though taking a large number of trees (several hundreds) eventually equalizes all performance; see Figure 18.

### A.2. Automatic selection of tuning parameters through 5-fold cross-validation

Even if the performance is not (much) sensitive to the choice of tuning parameters, we alleviate the burden of users by providing a fully automated procedure to select these parameters. This procedure uses two passes on the train data set: in the first pass (Steps 1 and 2 of Figure 20), it selects the tuning parameters through a 5-fold cross-validation estimation of performance in generalization (more detail are provided below). In the second pass (Step 3 of Figure 20), it fits the model on the entire train data set based on the selected tuning parameters. We do so to avoid over-fitting issues on the train data set: selecting the best tuning parameters on the train data set by comparing the performance of models fit on the entire train data set is prone to biases; indeed, with such a procedure, we would be comparing some in-sample errors rather than out-of-sample errors, which is what we need. Put differently, this simpler procedure would evaluate the respective performance of tuning parameters in too optimistic a way.

The first pass is a 5-fold cross-validation estimation of performance which consists of separating the train data set in a random partition with 5 folds (i.e., in 5 random non-overlapping subsets), fitting the model on 4 of them and evaluating the obtained performance on the 5th fold. This 5th fold varies, and we average out the five measures of performance obtained to determine the best tuning parameters.

The tuning parameters selected by this two-pass procedure were provided in Table 7. There is an important variability in the specific values selected for the pairs of tuning parameters by the subsets of variables considered. However, the performance of a pair of a given cell of Table 7 (i.e., for a given pair of a method plus subset of variables) is not even 0.1 s apart from the performance obtained by the pair of another cell in the same line of the table (i.e., for the same method but for a different subset

of variables). The seemingly instability of the values of the tuning parameters hides a remarkable stability in the underlying performance, which was already exhibited in the sensitivity analysis of Section A.1.

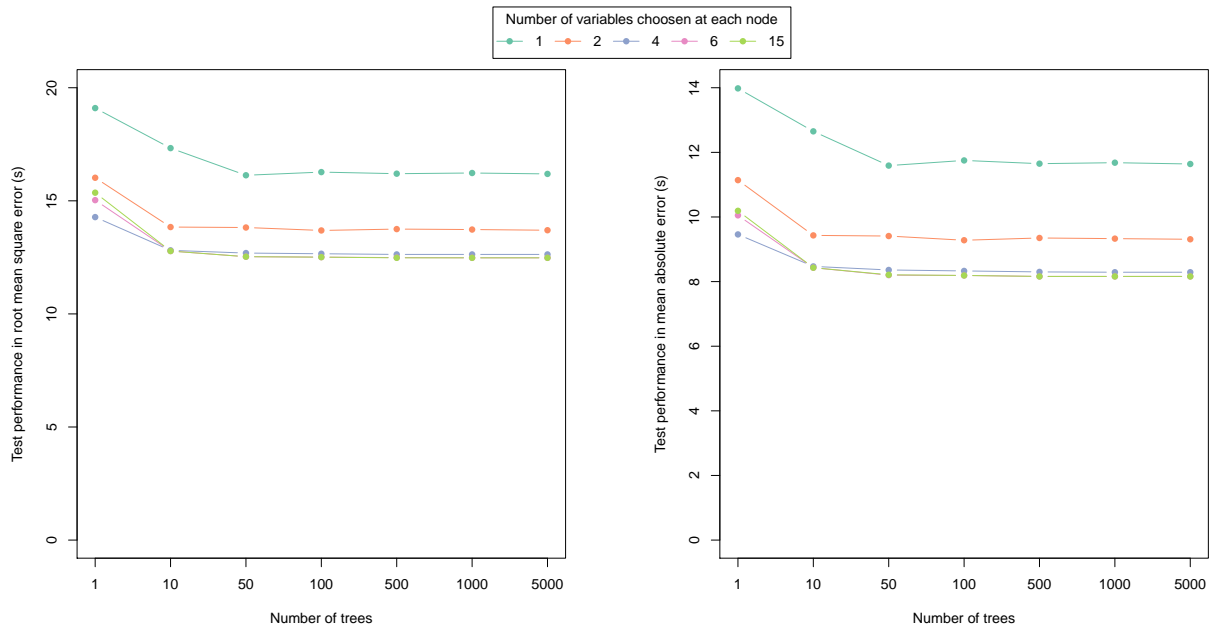


Figure 17: Performance of random forests on the test data set for various values of the pair  $(m, T)$  of tuning parameters, where  $m$  is the number of variables chosen at each split and  $T$  is the number of trees in the forest. The left picture measures performance in RMSE and the right picture does so in MAE.

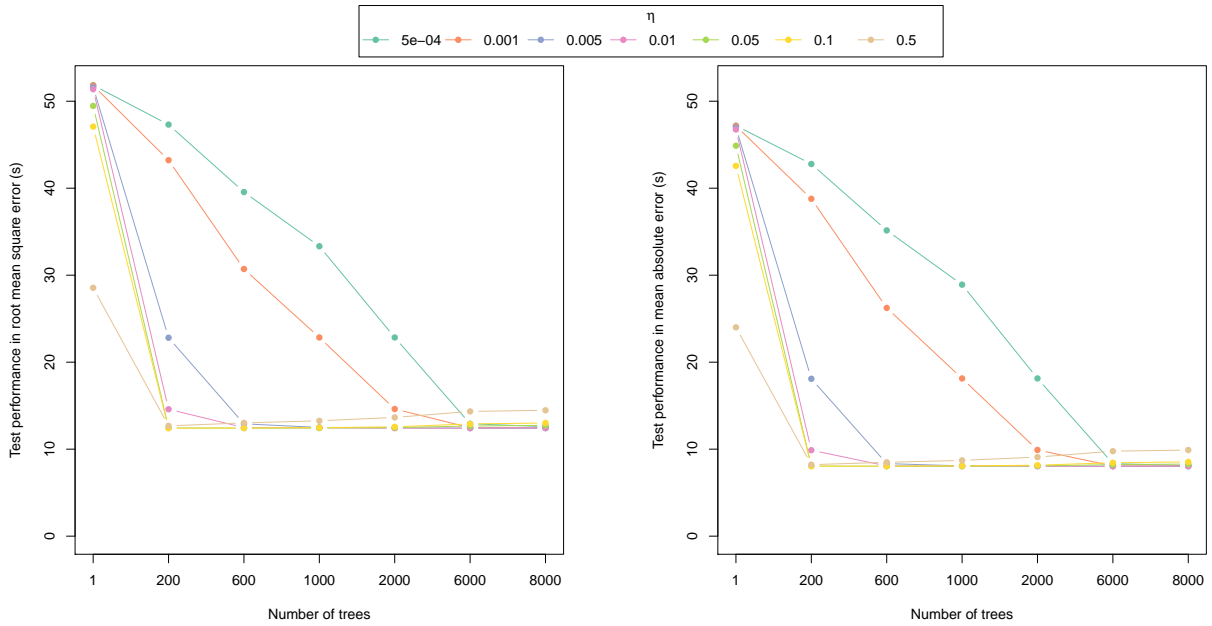


Figure 18: Performance of gradient boosting with regression trees on the test data set for various values of the pair  $(\eta, T)$  of tuning parameters, where  $\eta$  is the shrinkage parameter and  $T$  is the number of trees. The left picture measures performance in RMSE and the right picture does so in MAE.

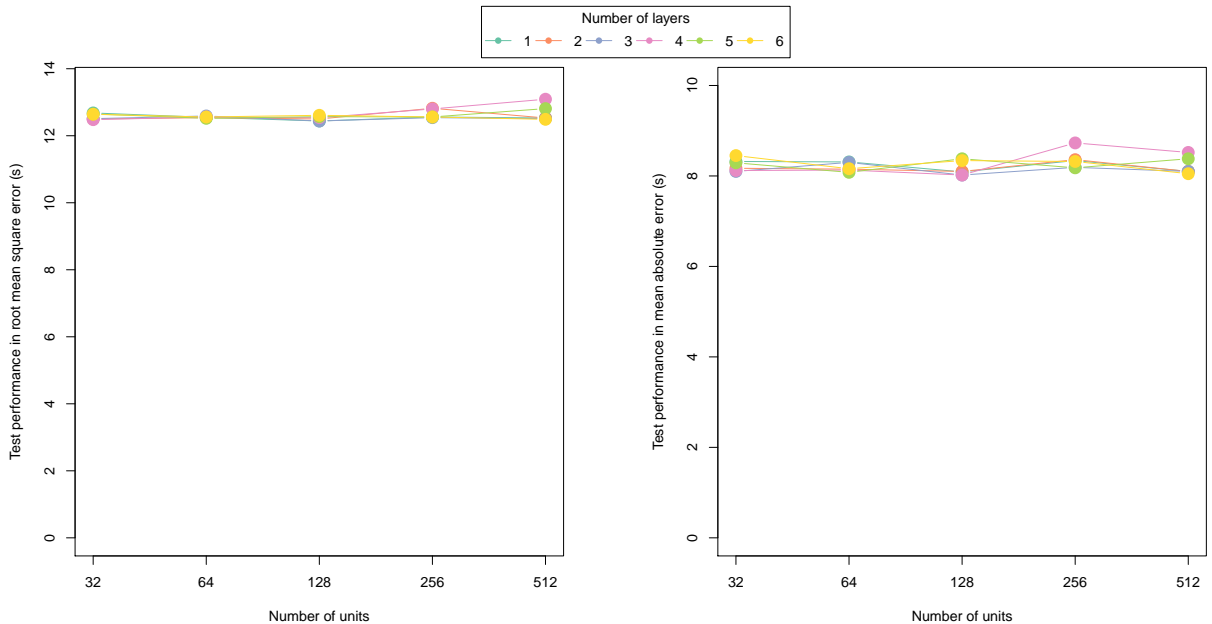


Figure 19: Performance of feed-forward neural networks on the test data set for various values of the pair  $(H, N)$  of tuning parameters, where  $H$  is the number of hidden layers and  $N$  is the number of nodes. The left picture measures performance in RMSE and the right picture does so in MAE.

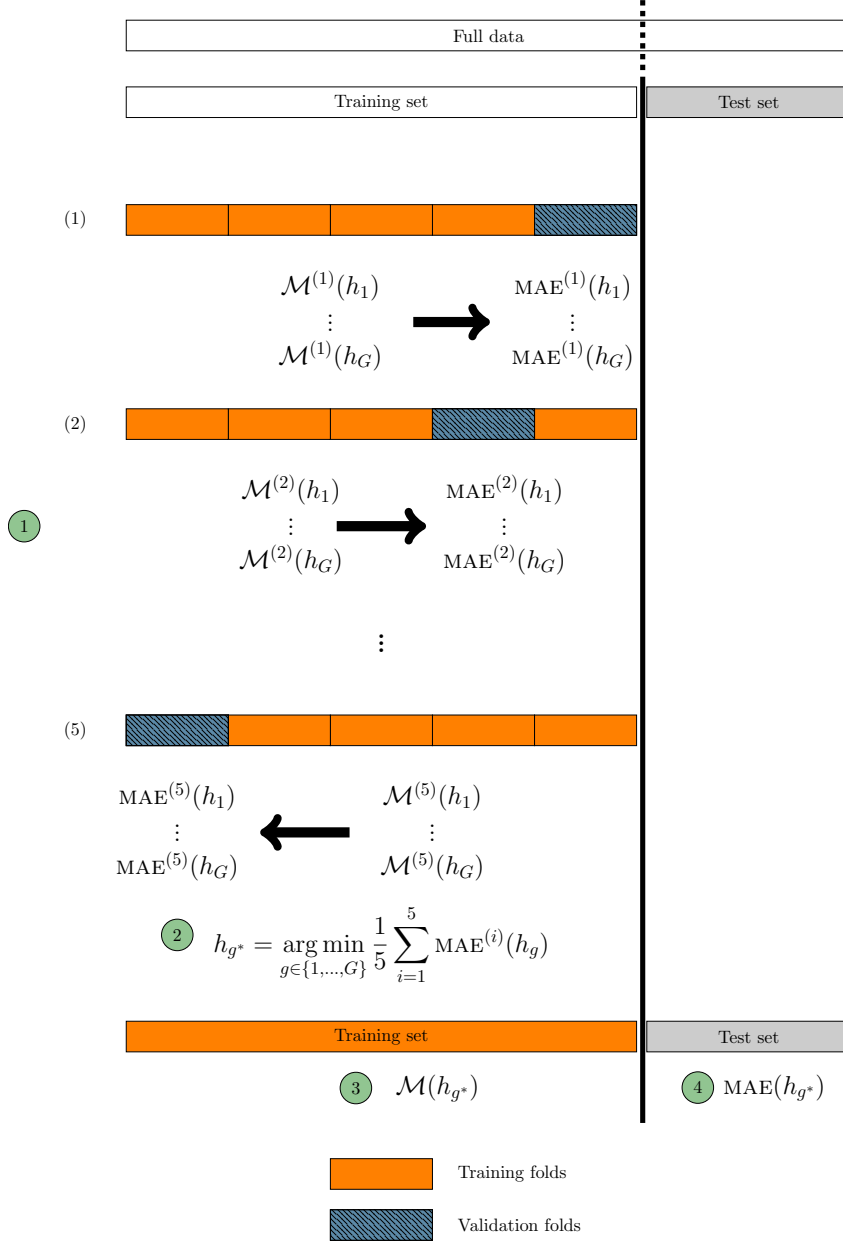


Figure 20: Principle of the automated selection procedure proposed, for a given machine-learning method. The full dataset is split into a training set (in orange) and a test set (in grey). The training set is itself split into a random partition consisting of 5 subsets called folds.

- ① For each pair of hyperparameters  $h_g$ , the model  $\mathcal{M}^{(i)}(h_g)$  is fit on all train data but the one of fold  $i$  and the performance  $\text{MAE}^{(i)}(h_g)$  is computed for this model on fold  $i$ .
- ② The performance in generalization of the method for hyperparameters  $h_g$  is estimated by averaging the five errors  $\text{MAE}^{(i)}(h_g)$ , for  $i \in \{1, \dots, 5\}$ . We then select the hyperparameters  $h_{g^*}$  minimizing  $\text{MAE}(h_g)$ .
- ③ Model  $\mathcal{M}(h_{g^*})$  is fit on the entire train data set.
- ④ We compute and report the performance of  $\text{MAE}(h_{g^*})$  of the model  $\mathcal{M}(h_{g^*})$  on the test data set.

## B. Robustness checks

In this section, we discuss the robustness of our results: when the differences  $y^{\text{obs}} - y^{\text{theo}}$  to the scheduled dwell time are modeled in lieu of the observed dwell times  $y^{\text{obs}}$ , still on line L (Section B.1); and what happens for the other line considered, line H (Section B.2).

### B.1. Modeling the differences $y^{\text{obs}} - y^{\text{theo}}$ to the scheduled dwell time

So far, we modeled directly the observed dwell time  $y^{\text{obs}}$ . We now look instead into the modeling of the deviations  $\Delta y = y^{\text{obs}} - y^{\text{theo}}$  to the scheduled dwell time  $y^{\text{theo}}$ , i.e., we run the methods discussed in Section 3 to model  $\Delta y$  (with newly optimized hyperparameters determined by following the methodology described in Section 3.6 and Appendix A.2). We obtain modelings  $\widehat{\Delta y}$  which we turn into modelings  $\hat{y}^{\text{obs}}$  of the observed dwell time by adding  $y^{\text{theo}}$ .

We observe in Table 11 (absolute performance of this modeling of the deviations) and in Table 12 (difference in modeling performance between direct modeling of  $y^{\text{obs}}$  and modeling of the deviations  $\Delta y$ ) that the two approaches yield extremely similar results, except when run on the PF variables in isolation, where the modeling of deviations is significantly more efficient. About 1 s of reduction in average modeling errors is gained. This was expected as modeling  $\Delta y$  amounts to using the RO variable  $y^{\text{theo}}$ , which we identified as a key determinant of the observed dwell time (see, e.g., Section 4.5).

In the main body of the article, we rather performed a direct modeling of  $y^{\text{obs}}$  to be able to report some “pure” performance for the PF variables.

### B.2. Results for line H—in brief

The main body of this article considered a specific sub-branch of line L (see Figure 2), and we now study what happens for the sub-branch of line H for which data is also available (see also Figure 2). This sub-branch features 11 stations on top of the origin and terminus stations. The same time period is considered as for line L and 145,609 triplets  $(k, s, d)$  are available. We may define similarly regimes of punctuality and regimes of affluence (based on thresholds  $\leq 53$  and  $\geq 54$  passengers), and obtain the breakdown summarized in Table 13.

We (re-)optimized the hyperparameters of random forests on this new data set, following the methodology described in Section 3.6 and Appendix A.2, and provide in Table 14 (the counterpart of Table 10) the modeling performance of the dwell time for random forests, globally or by the regimes of punctuality or affluence.

Table 14 confirms that railway operations [RO] variables are more useful for the modeling than passenger flow [PF] variables, with a difference in performance of about 2 s. This was expected. The true confirmation expected was on the improvement of RO and PF variables considered simultaneously (possibly together with the affluence M at the critical door) over RO variables used in isolation: we get a mixed picture of virtually no improvement in most situations, except for late trains and in case of a high affluence, where improvements of about 0.3 s are obtained. The patterns observed are therefore similar to the ones of Table 10, but take place with a lower intensity.

Figures 22 and 23 further illustrate these (more moderate) improvements in the modeling performance: no significant improvements are observed when observations are broken down by affluence regimes (Figure 23) while significant improvements are observed only in the case of late trains (Figure 22), with a significant worsening for a tiny fraction of the observations is simultaneously observed for early trains. All in all, the existence of improvements only for the most challenging situation of late trains and their smaller intensity may be caused by the absence of peaks of affluence on line H (see Figure 21), while such peaks exist for line L.

Table 11: Modeling performance for the observed dwell time  $y^{\text{obs}}$  based on a modeling of the deviation  $\Delta y = y^{\text{obs}} - y^{\text{theo}}$ : results are formatted as in Tables 8 and 10, with standard errors still smaller than 0.03 seconds.

Methods	MAE				RMSE			
	PF	RO	RO PF	RO PF+M	PF	RO	RO PF	RO PF+M
1. Linear regression with additive effects	12.4	10.5	10.2	10.1	16.9	14.8	14.5	14.3
2. Linear regression with a multiplicative effect of $\Delta a$ by $z$	12.4	9.1	8.9	8.8	16.9	13.6	13.2	13.1
3. Linear regression with multiplicative effects by triplets	12.2	8.8	8.3	8.3	16.7	13.2	12.6	12.5
4. Random forests	12.5	8.5	8.1	8.0	17.1	13.1	12.4	12.3
5. Gradient boosting with regression trees	12.0	8.5	8.0	7.9	16.5	13.0	12.4	12.2
6. Feed-forward neural networks	11.9	8.5	7.9	7.9	16.4	13.0	12.4	12.3
<i>Random forests</i>								
Early trains	15.4	7.9	8.0	7.9	21.0	12.5	12.6	12.4
Trains on time	11.8	8.3	7.8	7.8	16.2	12.4	11.9	11.7
Late trains	12.7	9.7	8.5	8.5	17.2	14.2	12.9	12.7
<i>Random forests</i>								
Low affluence	12.4	7.6	7.5	7.5	16.9	11.4	11.3	11.4
High affluence	15.0	9.2	8.7	8.5	20.5	14.3	13.5	13.1



Table 12: Differences in modeling performance between Table 11 (based on a modeling of the deviation  $\Delta y = y^{\text{obs}} - y^{\text{theo}}$ ) and Tables 8 and 10 (based on a direct modeling of  $y^{\text{obs}}$ ). Negative numbers indicate a more accurate modeling in Table 11.

Methods	MAE				RMSE			
	PF	RO	RO PF	RO PF+M	PF	RO	RO PF	RO PF+M
1. Linear regression with additive effects	-1.3	0.0	0.0	0.0	-1.5	0.0	0.0	0.0
2. Linear regression with a multiplicative effect of $\Delta a$ by $z$	-1.3	0.0	0.0	0.0	-1.5	0.0	0.0	0.0
3. Linear regression with multiplicative effects by triplets	-1.1	0.0	0.0	0.0	-1.3	0.0	0.0	0.0
4. Random forests	-1.2	0.1	0.0	0.0	-1.7	0.2	-0.1	0.0
5. Gradient boosting with regression trees	-0.9	0.0	0.0	0.0	-1.4	0.0	0.0	0.0
6. Feed-forward neural networks	-0.8	0.1	-0.1	-0.1	-1.0	0.0	0.0	0.1
<i>Random forests</i>								
Early trains	-1.8	0.0	-0.1	0.0	-2.3	0.2	-0.1	0.0
Trains on time	-0.8	0.0	0.0	0.0	-1.0	0.1	0.0	0.0
Late trains	-0.7	0.2	0.1	0.0	-0.9	0.3	0.1	0.0
<i>Random forests</i>								
Low affluence	-1.1	0.1	-0.1	0.0	-1.5	0.2	0.0	0.0
High affluence	-1.4	0.1	0.0	0.0	-1.8	0.2	0.0	0.0

Table 13: Breakdown of the data set for line H by regimes of punctuality or affluence.

Punctuality	Early: 33,448	On time: 58,755	Late: 53,406
Affluence	Low: 72,795	High: 72,814	

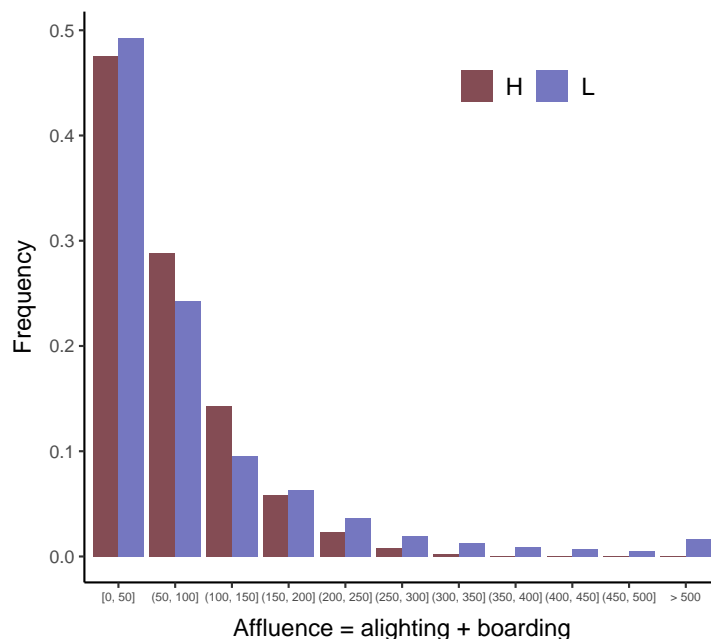


Figure 21: Histograms of affluence (numbers of passengers alighting and boarding, for all stations and all trains considered) for lines H and L.

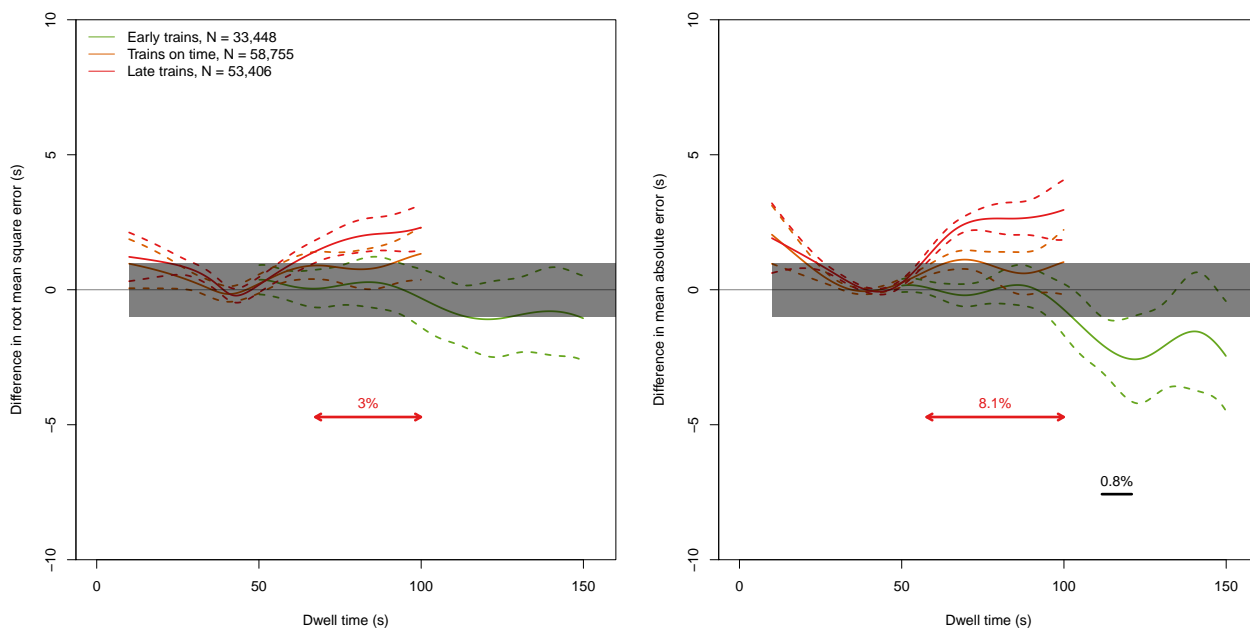


Figure 22: Differences in mean square errors (left graph) and absolute errors (right graph) between RF-RO and RF-All for the modeling of dwell time ( $y$ -axis) by observed dwell time ( $x$ -axis), factored by regimes of punctuality. Positive numbers correspond to the superiority of RF-All over RF-RO.

Table 14: Modeling performance of the dwell time for random forests by regimes of punctuality or regimes of affluence (lines) and for each subset of variables (rows); see the legend of Table 8), in MAE (*left part of the table*) and RMSE (*right part of the table*). Standard errors are smaller than 0.03 seconds.

Random forests	MAE				RMSE			
	PF	RO	RO PF	RO PF+M	PF	RO	RO PF	RO PF+M
All trains	10.6	8.0	7.9	7.8	15.1	11.9	11.7	11.6
Early trains	13.2	7.8	7.9	7.9	19.2	11.9	11.9	11.9
Trains on time	9.6	7.8	7.7	7.6	13.4	11.6	11.5	11.4
Late trains	10.1	8.4	8.1	8.0	13.8	12.3	12.0	11.8
Low affluence	9.9	7.5	7.4	7.4	13.7	10.9	10.8	10.8
High affluence	11.3	8.5	8.4	8.2	16.4	13.0	12.6	12.5

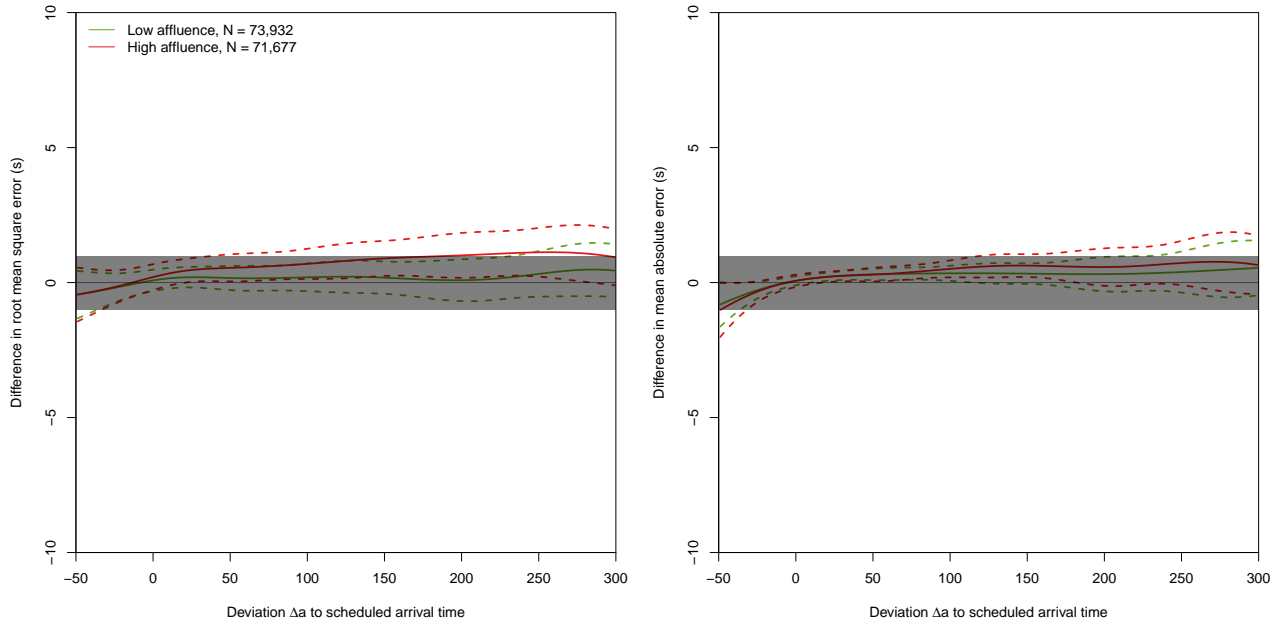


Figure 23: Differences in mean square errors (left graph) and absolute errors (right graph) between RF-RO and RF-All for the modeling of dwell time ( $y$ -axis) by deviation  $\Delta a$  to scheduled arrival time ( $x$ -axis), factored by regime of affluence. Positive numbers correspond to the superiority of RF-All over RF-RO.