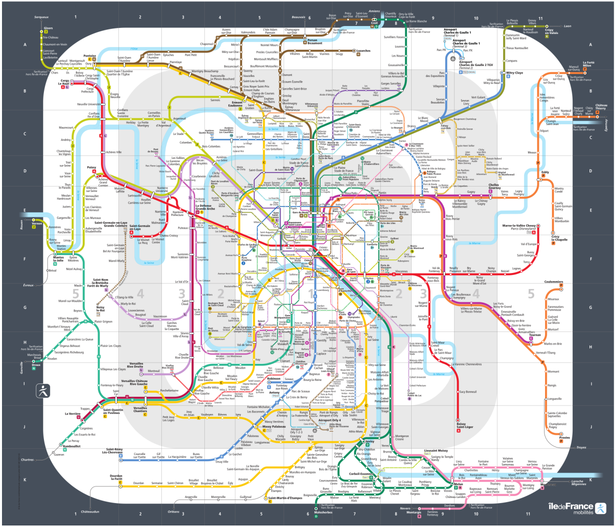
Modeling and forecasting of railway operation variables and passenger flows for dense traffic areas

PhD Defence

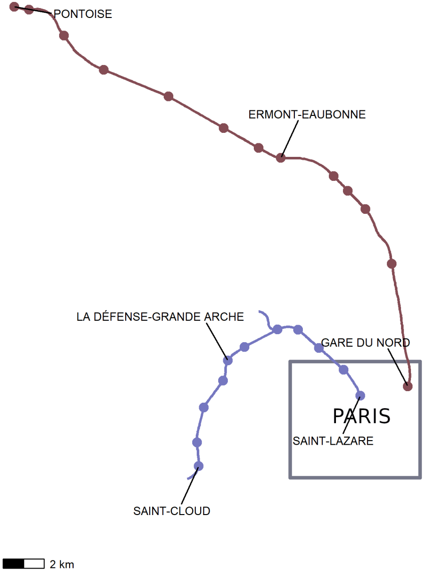
Rémi Coulaud
supervised by Gilles Stoltz and Christine Keribin

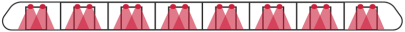
30^{th} November 2022



3.4M passengers/day, more than 6 200 trains/day

Perimeter and data



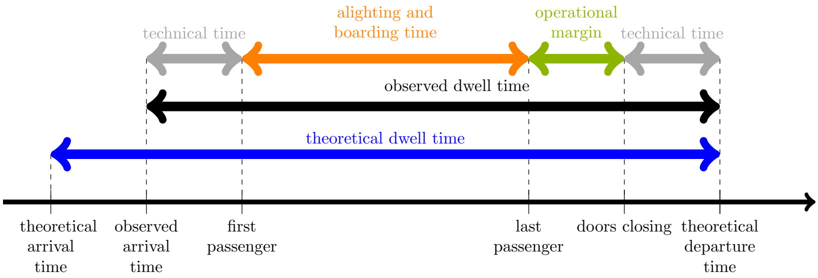


Passenger flow measure: APC (**PF**)

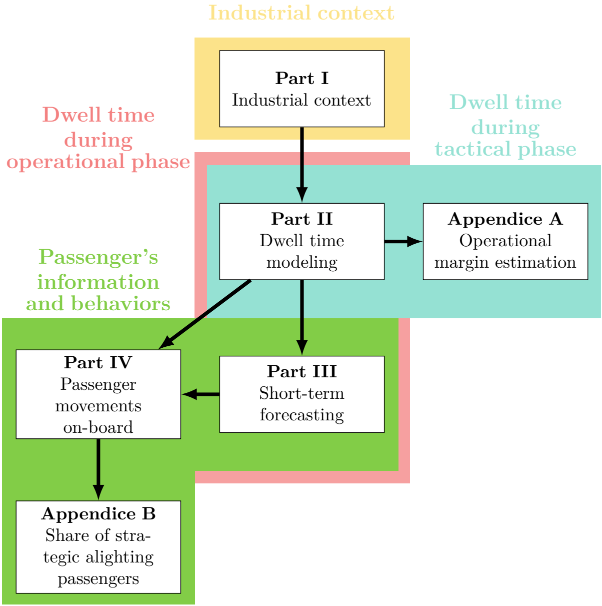
Coverage rate in 

	2019	2022
H	100%	100%
L	80%	100%

Dwell time for commuter trains

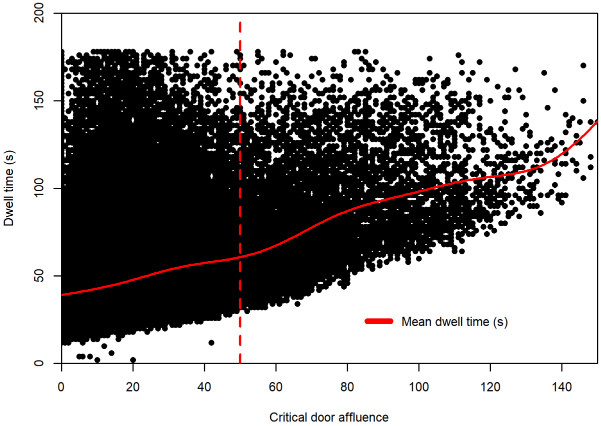


- theoretical times are fixed 2 years in advance
- 20-30% of the total travel time is spent at stops


Industrial context
Part I
Industrial context
Dwell time
during
operational phase
Dwell time
during
tactical phase
Part II
Dwell time
modeling
Appendice A
Operational
margin estimation
Passenger's
information
and behaviors
Part IV
Passenger
movements
on-board
Part III
Short-term
forecasting
Appendice B
Share of stra-
tegic alighting
passengers

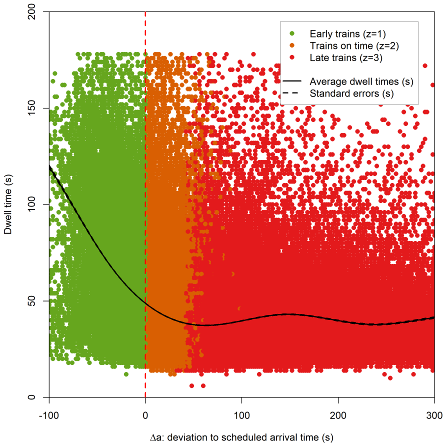
Passenger impact on dwell time in a railway context

Lam *et al.* [10] build a metro dwell time regression model using only passenger flow variables (**PF**)



Arrival delay effect on dwell time in a railway context

Kecman & Goverde [9] build a random forests using only railway operation variables (**RO**)



A unique data set with accurate PF + RO + M variables

	Variable	Domain	Notation
	Observed dwell time	{0, 2, ..., 180}	$Y^{\text{obs}} = d^{\text{obs}} - a^{\text{obs}}$
PF	Boarding numbers	$\{0, 1, \ldots\}$	B
	Alighting numbers	$\{0, 1, \ldots\}$	A
	Train crowding	[0, 2]	$C = L/\text{cap}$
M	Critical door affluence	$\{0, 1, \ldots\}$	M
RO	Theoretical dwell time	{0, 10, ..., 180}	$Y^{\text{theo}} = d^{\text{theo}} - a^{\text{theo}}$
	Arrival delay	[−600, 600]	$\Delta a = a^{\text{obs}} - a^{\text{theo}}$
	Type	{simple, double}	T

Only Palmqvist *et al.* [13] and Cornet *et al.* [2] have access to **RO+PF**

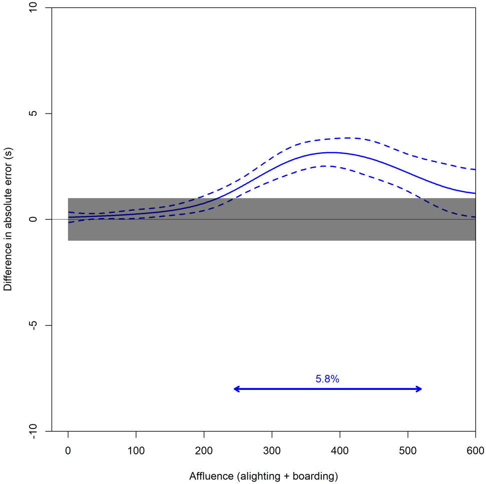
Global performance: mean absolute errors (MAE)

Lines	L			H		
Variables	PF	RO	RO+PF+M	PF	RO	RO+PF+M
1. LM: with interactions	13.3	8.8	8.3	12.2	8.8	8.3
2. Random forests	13.7	8.4	8.0	12.5	8.5	8.0

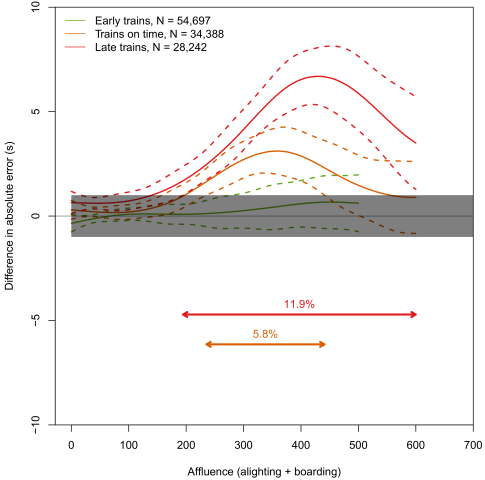
- Variables: **PF** $\ll$ **RO** $\leq$ **RO+PF+M**
- Perimeter: line L is more challenging than line H

Local performance

Difference in absolute error: $|Y - \hat{Y}_{RO}| - |Y - \hat{Y}_{RO+PF+M}|$

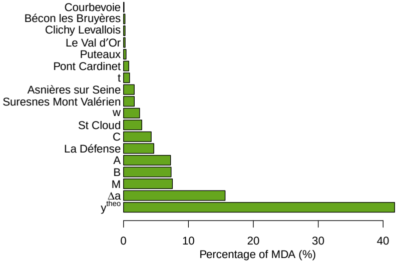


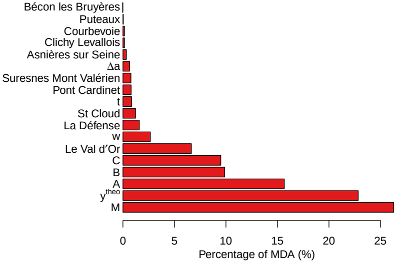
Local performance by punctuality regimes



A passenger flow effect on late trains which confirms Pedersen *et al.* [14] and Medeossi & Nash [12] intuitions

Variables importance





Early trains = $\Delta a, y^{theo}$ railway operation **(RO)**

Late trains = M, A, B passengers flow variables **(PF)**

Modelling → forecasting

$$\hat{Y}_{t+1} = \hat{f}(\underbrace{A_{t+1}, B_{t+1}, C_{t+1}, \Delta A_{t+1}}_{\text{not known at t+1}}, \underbrace{Y^{\text{theo}}_{t+1}, T_{t+1}, \ldots}_{\text{known at t+1}})$$

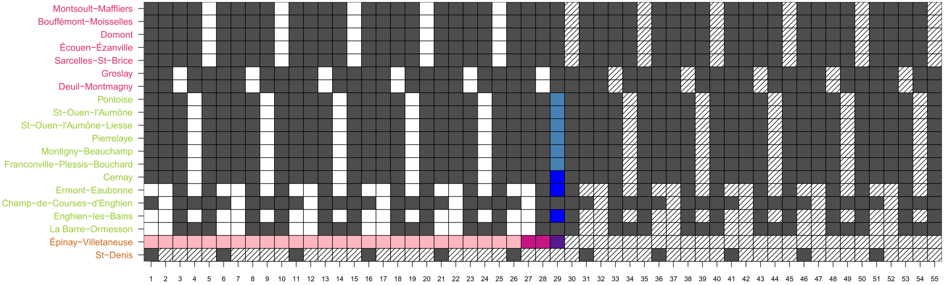
Strategy : Forecast A_{t+1}, B_{t+1}, C_{t+1} and ΔA_{t+1} with an auto-regressive strategy + plug in

also used to forecast Y_{t+1}

Real-time information

Real-time crowding and delay information require forecasting

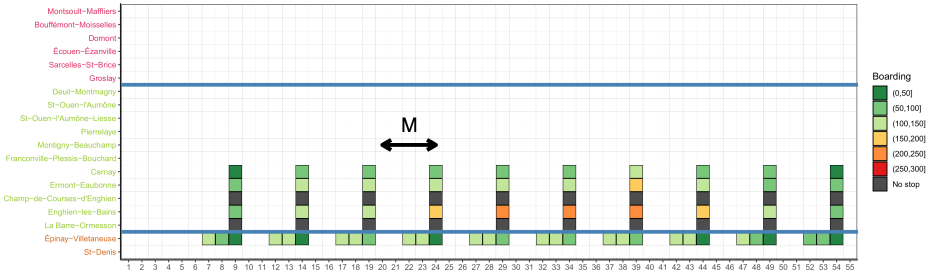
Bi-autoregressive and non-stationary model



Inspired from Corman & Kecman [1], Bayesian forecasting model using the recent past along the train ride and the recent past at the station

$$x_{k,s} = \beta_{k,s}^{0,0} + \sum_{p=1}^{P} \beta_{k,s}^{p,0} x_{k-p,s} + \sum_{q=1}^{Q} \beta_{k,s}^{0,q} x_{k,s-q} + \varepsilon_{k,s}$$

Pattern and stationary model



$$x_{k,s} = \beta^{0,0}_{k[M],s} + \sum_{p=1}^{P} \beta^{p,0}_{k[M],s} x_{k-p,s} + \sum_{q=1}^{Q} \beta^{0,q}_{k[M],s} x_{k,s-q} + \varepsilon_{k,s}$$

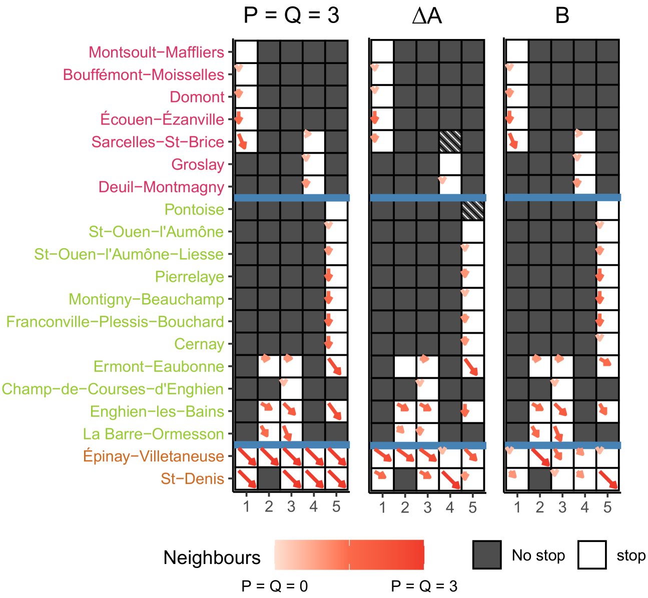
Pattern models are in between Li *et al.* [11] too frugal dwell time models and Corman & Kecman [1] too complex delays models

Global performance: mean absolute errors (MAE)

Models			Railway Operation **(RO)**		Passenger Flow **(PF)**		
Name	L-shape	Number of parameters	Y^{obs} [s]	ΔA [s]	A [pas]	B [pas]	L [pas]
Non-stationary	P = Q = 0	337	9.7	35.8	10	21	69
	P = Q = 1	956	9.5	16.1	9	18	20
Semi-stationary	P = Q = 1	417	9.3	18.6	10	19	23
	P = Q = 2	455	9.2	18.1	9	19	23
	P = Q = 3	482	9.2	18.1	9	18	23
Stationary	P = Q = 1	80	9.3	16.2	10	21	27
	P = Q = 2	118	9.2	15.8	8	20	27
	P = Q = 3	145	9.2	15.9	8	20	27

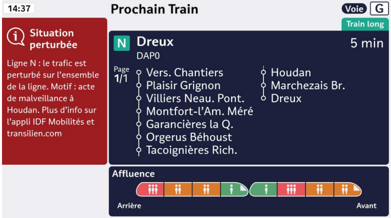
- For ΔA and L: $(P = Q \geq 1) \gg (P = Q = 0)$
- Stationary $\geq$ non-stationary for **(RO)**
- Semi-stationary $\approx$ non-stationary for **(PF)**

Neighbourhood automatic selection



- Stop specific L-shape neighbourhood
- B needs a shallower neighbourhood than ΔA

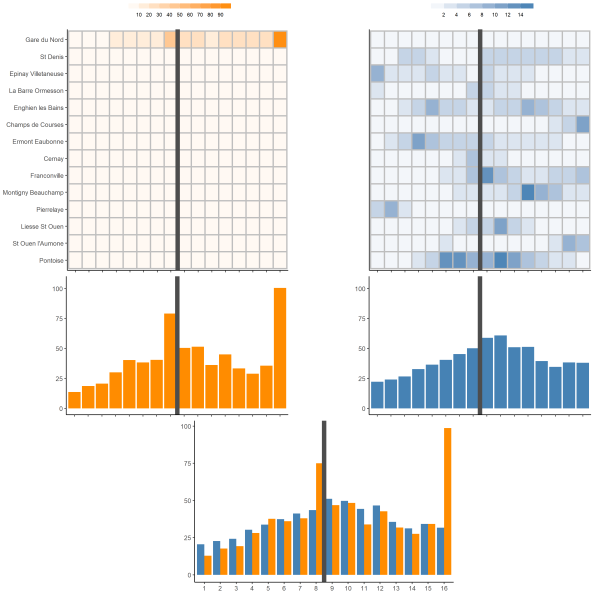
Real-time crowding information (RTCI)



RTCI on station screen based on **APC (alighting and boarding passengers)**

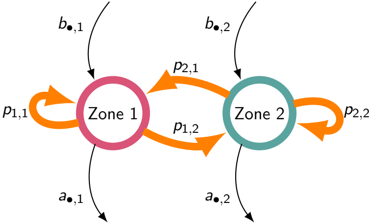
100m open gangway units

From station scale to trip scale



- Alighting and boarding distribution **imbalance** at the **trip scale**

Zone definition and notations



Notation	Description
$p_{i,j}$	probability to board zone i to move to zone j
$b_{\bullet,i}$	number of passengers boarding zone i
$a_{\bullet,i}$	number of passengers alighting from zone i

Models

Minimum least square (MLS)

$$\underset{\boldsymbol{P}}{\operatorname{argmin}} \quad \sum_{(k,d)\in\mathcal{N}} \left\| \boldsymbol{a}_{\bullet}^{k,d} - \boldsymbol{b}_{\bullet}^{k,d} \boldsymbol{P} \right\|_2^2$$

Maximum likelihood estimation (MLE)

$$\underset{\boldsymbol{P}}{\operatorname{argmax}} \quad \sum_{(k,d)\in\mathcal{N}} \sum_{j=1}^{I} a_{\bullet,j}^{k,d} \log\left(\sum_{i=1}^{I} r_{\bullet,i}^{k,d} p_{i,j} \right)$$

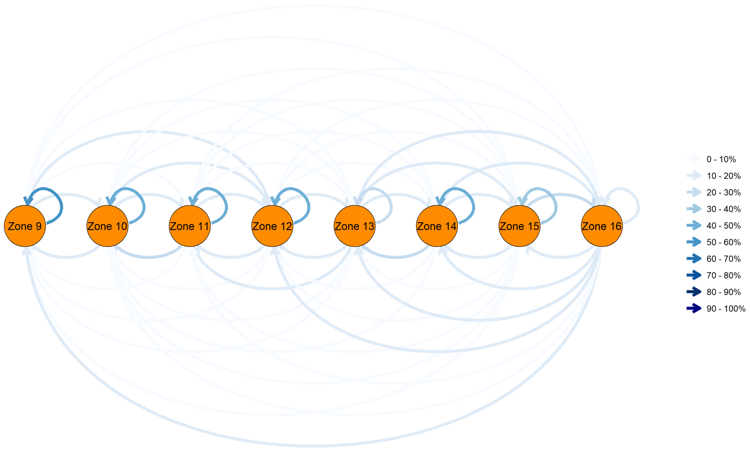
under the constraint of $\boldsymbol{P}$ being stochastic

Global performance

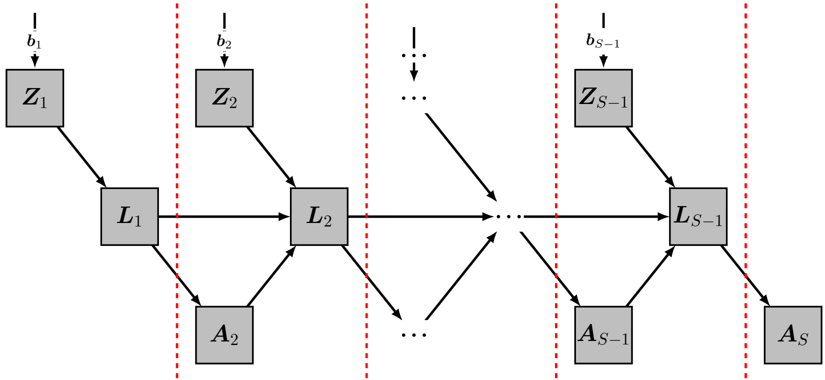
Models	Front MAE [pas]	Back MAE [pas]
Without movement	10.9	17.5
$\widehat{\boldsymbol{P}}_{\mathrm{MLS}}$	6	8.5
$\widehat{\boldsymbol{P}}_{\mathrm{MLE}}$	6	8.5

Without movement $\ll \widehat{\boldsymbol{P}}_{\mathrm{MLS}} = \widehat{\boldsymbol{P}}_{\mathrm{MLE}}$

Transition matrix



Models: station scale



- $\boldsymbol{Z}_s$ hidden passenger movements at station s
- $\boldsymbol{L}_s$ hidden load after departure at station s

Main contributions

Dwell time modelling:

Rémi Coulaud, Christine Keribin, and Gilles Stoltz. Modeling dwell time in a data-rich railway environment: with operations and passenger flows data.
Re-submitted *Transportation Research Part C* (TRC) after corrections. Preprint accessible here `hal.archives-ouvertes.fr/hal-03651835/`, 2022

Rémi Coulaud and Martine Grangé. Modélisation de l'impact des flux voyageurs sur les temps d'échange pour la simulation des marges d'exploitation : une application à la ligne N de transilien.
In *4èmes Rencontres Francophones Transport Mobilité (RFTM)*, 2022

Short-term forecasting:

Rémi Coulaud, Christine Keribin, and Gilles Stoltz. One-station-ahead forecasting of dwell time, arrival delay and passenger flows on trains equipped with automatic passenger counting (apc) device.
In *13th World Congress on Rail Research (WCRR)*, 2022

Passenger's movement on board:

Rémi Coulaud and Mathilde Vimont. How to use APC data to model passenger movement on-board? An application to Paris suburban train network.
In *8th International Symposium On Transport Network Reliability (INSTR)*, 2021

Rémi Coulaud, Valentine Mazon, Laura Sanchis, and Oded Cats. Share of strategic alighting passengers combining automatic passenger counting and OpenStreeMap.
In *Conference on Advanced Systems in Public Transport (CASPT)*, 2022

Perspectives

Dwell time during tactical phase:

- Propose an extended definition of critical door
- Develop a method to compute theoretical dwell time margins

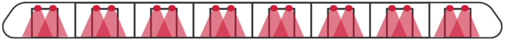
Dwell time during operational phase:

- Forecast dwell time with a plug-in strategy
- Test wider forecasting ranges ($s+2$, $s+3$, $s+4$, $\ldots$)
- Write a literature review on short-term crowding forecasting

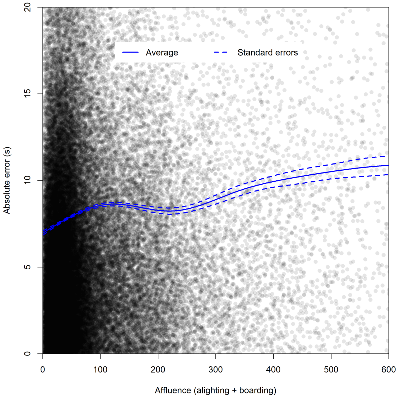
Passenger's information and behaviour:

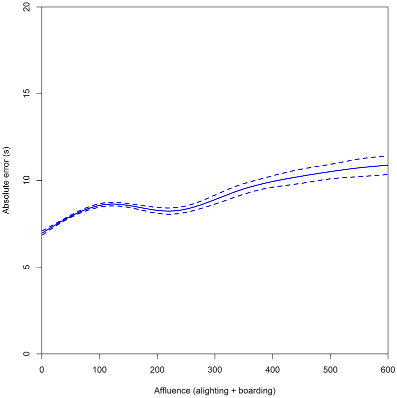
- Test the station scale model

Thank you



Conditional mean



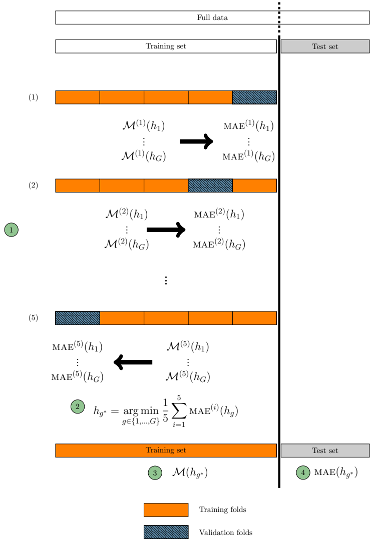


Variable importance: mean decrease accuracy

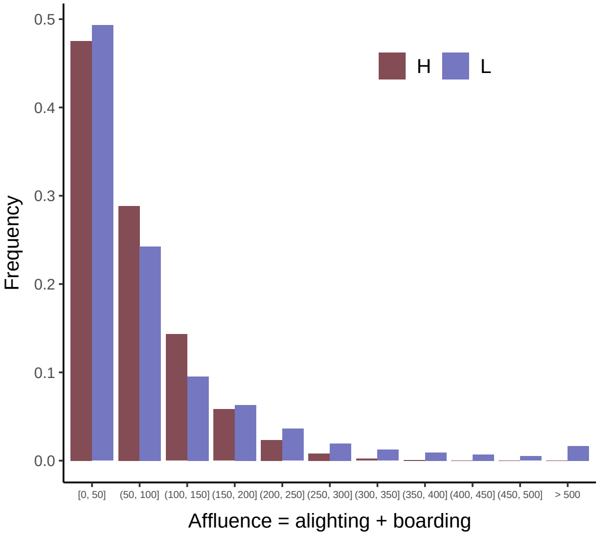
- Bootstrap data with replacement into T data sets
- Compute a random forest based on each of these T bootstrapped data sets
- Randomly permuting the values of the variable of interest
- Compute on out-of-bag observations the difference of average squared error between permuted and original data

$$\frac{\mathrm{MDA}_j}{\sum_{i=1}^{p} \mathrm{MDA}_i}$$

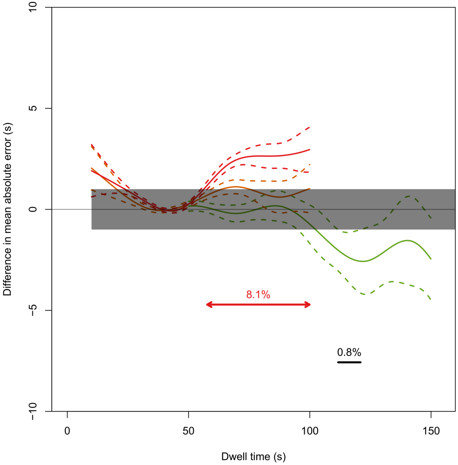
Cross-validation strategy



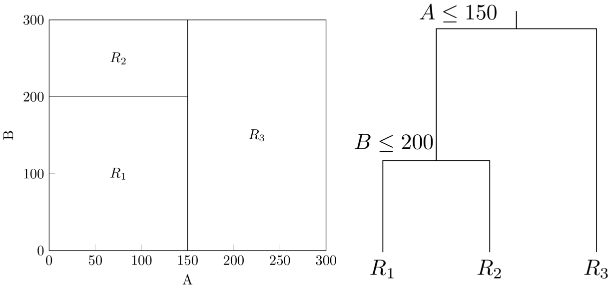
Line L v.s. line H



Line H - local performance by regimes

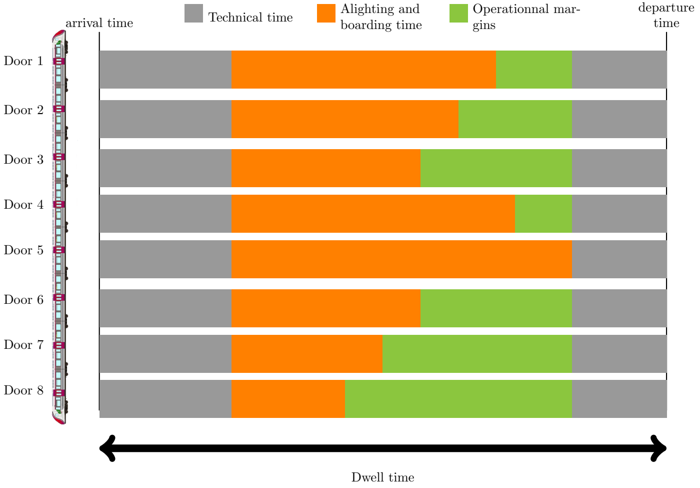


Regression tree

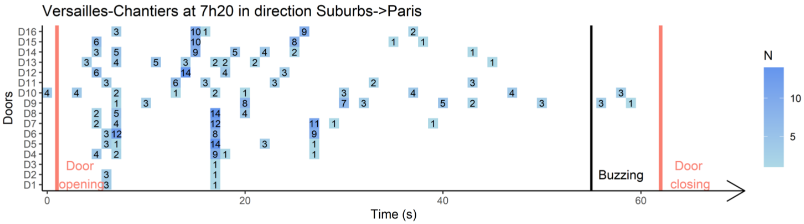


- Only alighting and boarding passengers number to explain dwell time
- Three different dwell times for three different regions and two splits

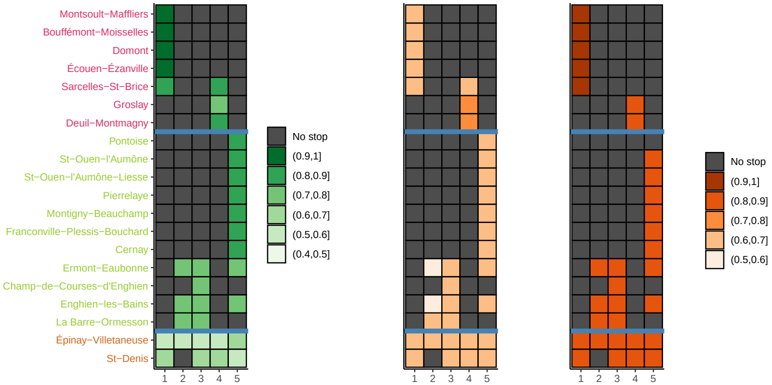
An illustration of critical door effect



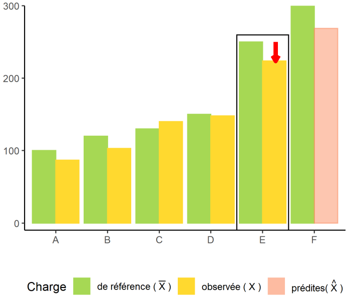
Very accurate automatic passenger counting data

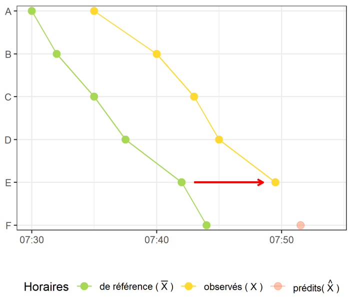


Consistency of the neighbourhood order

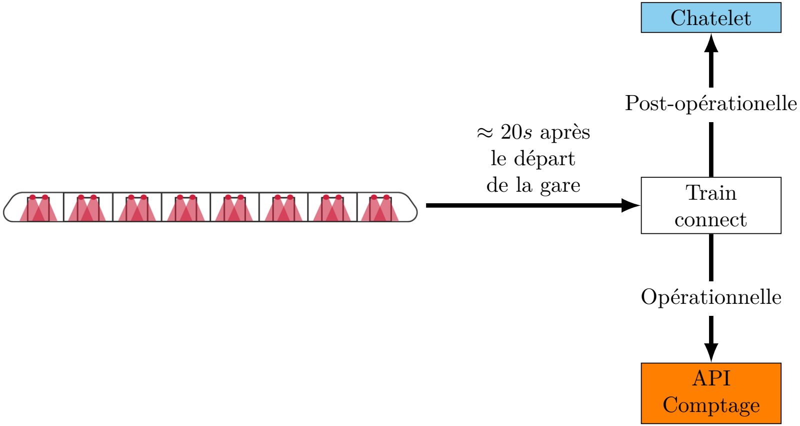


SNCF forecasting model

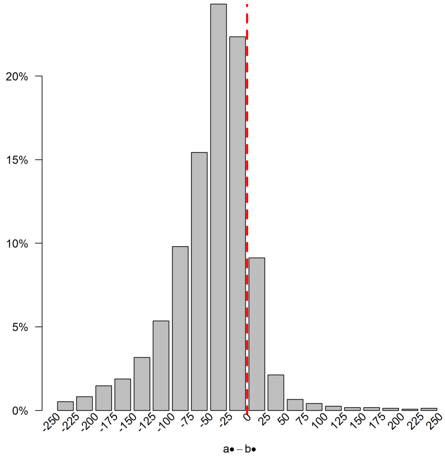




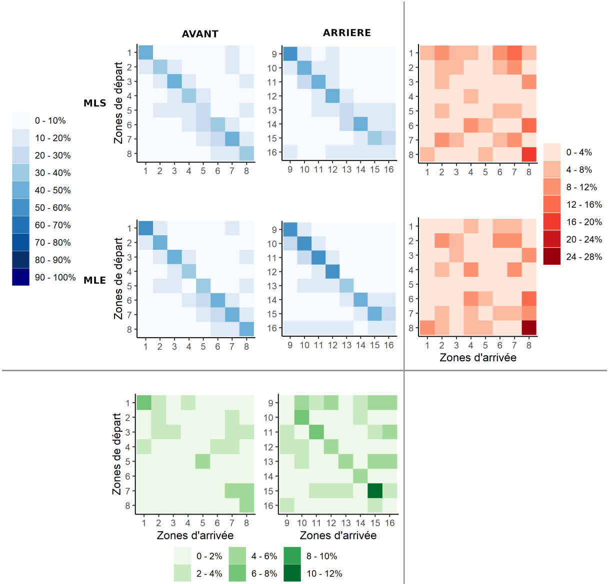
Data quality - I



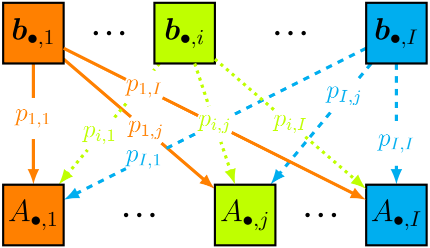
Data quality - II



Transition matrices comparisons



Probabilistic model at the trip scale - I



We define :

$$\boldsymbol{U}_{\bullet,i} \sim \mathcal{M}(b_{\bullet,i}, p_{i,1}, \ldots, p_{i,I}).$$

Then, we define:

$$\boldsymbol{A}_{\bullet} = \sum_{j=1}^{I} \boldsymbol{U}_{\bullet,j}.$$

Probabilistic model at the trip scale - II

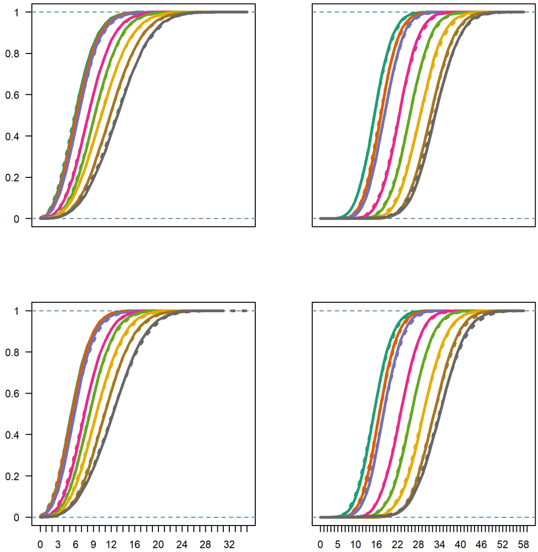
Approximation

The random law of $\boldsymbol{A}_\bullet$ *is approached by:* $\mathcal{M}(b_{\bullet,\bullet}, \pi_{\bullet,1}, \ldots, \pi_{\bullet,I})$ *with* $\pi_{\bullet,j} = \sum_{i=1}^{I} r_{\bullet,i} p_{i,j}$ *where* $r_{\bullet,i} = b_{\bullet,i}/b_{\bullet,\bullet}$.

The probability distribution of the alighting numbers is :

$$\mathbb{P}(\boldsymbol{A}_\bullet = \boldsymbol{a}_\bullet ; \boldsymbol{b}_\bullet) = \prod_{j=1}^{I} \frac{b_{\bullet,\bullet}!}{a_{\bullet,j}!} \left(\sum_{i=1}^{I} r_{\bullet,i} p_{i,j} \right)^{a_{\bullet,j}} .$$

Approximation quality



Probabilistic model at the station scale - hypothesis

(A_0) Trips are repeated according to day d and train k.

For a trip (k, d) :

(A_{1a}) Passenger movements conditionally to boarding follow :

$$\boldsymbol{W}_s^{k,d} \sim \mathcal{M}(b_{s,\bullet}^{k,d}, \pi_{s,1}^{k,d}, \dots, \pi_{s,I}^{k,d}), \quad s = 1, \dots, S-1,$$

where $\pi_{s,j}^{k,d} = \sum_{i=1}^{I} r_{s,i}^{k,d} p_{s,i,j}$ with $r_{s,i}^{k,d} = b_{s,i}^{k,d} / b_{s,\bullet}^{k,d}$.

(A_{1b}) Passenger movements at the different stations $\boldsymbol{W}_s^{k,d}$, $s = 1, \dots, S-1$, are independent to boarding and other passenger movement's at other stations $s' \neq s$.

(A_{2a}) The probability distribution of alighting numbers of zone i at station s conditionally to the past is only dependant of the load entering station s :

$$\mathbb{P}\left(A_{s,i}^{k,d} \middle| a_{2:(s-1),i}^{k,d}, z_{1:(s-1),i}^{k,d}\right) = \mathbb{P}\left(A_{s,i}^{k,d} \middle| \ell_{s-1,i}^{k,d}\right), \quad s = 2, \dots, S.$$

(A_{2b}) The alighting numbers of zone i at station s conditionally to load $\ell_{s-1,i}^{k,d}$ leaving station $s-1$ follow a binomial distribution :

$$A_{s,i}^{k,d} \sim \mathcal{B}(\ell_{s-1,i}^{k,d}, \alpha_{s,i}), \quad s = 2, \dots, S-1.$$

(A_{2c}) For all stations s, the vector of alighting numbers $\boldsymbol{A}_s^{k,d}$ for this station is independent conditionally to the load $\boldsymbol{\ell}_s^{k,d}$.

Probabilistic model at the station scale - Log-likelihood

$$\mathbb{P}\left(\boldsymbol{a}_{2:S}, \boldsymbol{w}_{1:(S-1)}; \boldsymbol{b}_{1:(S-1)}, \boldsymbol{\theta}\right)$$
$$= \prod_{s=2}^{S} \underbrace{\left(\prod_{i=1}^{I} \binom{\ell_{s-1,i}}{a_{s,i}} (\alpha_{s,i})^{a_{s,i}} (1-\alpha_{s,i})^{(\ell_{s-1,i}-a_{s,i})}\right)}_{\mathbb{P}(\boldsymbol{a}_s|\boldsymbol{\ell}_{s-1};\boldsymbol{\theta})}$$
$$\underbrace{\left(\prod_{i=1}^{I} \frac{(b_{s-1,\bullet}!)}{(w_{s-1,i}!)} (\pi_{s-1,i})^{w_{s-1,i}}\right)}_{\mathbb{P}(\boldsymbol{w}_{s-1};\boldsymbol{b}_{s-1},\boldsymbol{\theta})}. \quad (1)$$

Proof Log-likelihood - I

At the terminal station S, we have :

$$\mathbb{P}\Big(\boldsymbol{a}_{2:S}, \boldsymbol{w}_{1:(S-1)}; \boldsymbol{b}_{1:(S-1)}, \boldsymbol{\theta}\Big)$$

$$=\mathbb{P}\Big(\underbrace{\boldsymbol{a}_S}_{\text{Station S}} \;\Big|\; \underbrace{\boldsymbol{a}_{2:(S-1)}, \boldsymbol{w}_{1:(S-1)}}_{\text{values until station S-1}}; \boldsymbol{b}_{1:(S-1)}, \boldsymbol{\theta}\Big)$$

$$\mathbb{P}\Big(\boldsymbol{a}_{2:(S-1)}, \boldsymbol{w}_{1:(S-1)}; \boldsymbol{b}_{1:(S-1)}, \boldsymbol{\theta}\Big).$$

Then, we have :

$$\mathbb{P}\Big(\boldsymbol{a}_{2:(S-1)}, \boldsymbol{w}_{1:(S-1)}; \boldsymbol{b}_{1:(S-1)}, \boldsymbol{\theta}\Big)$$

$$= \mathbb{P}\Big(\boldsymbol{a}_{2:(S-1)}, \boldsymbol{w}_{1:(S-2)}; \boldsymbol{b}_{1:(S-1)}, \boldsymbol{\theta}\Big) \times \mathbb{P}\Big(\boldsymbol{w}_{S-1}; \boldsymbol{b}_{1:(S-1)}, \boldsymbol{\theta}\Big),$$

simplified with hypothesis (A_{1b}) :

$$\mathbb{P}\Big(\boldsymbol{w}_{S-1}; \boldsymbol{b}_{1:(S-1)}, \boldsymbol{\theta}\Big) = \mathbb{P}\Big(\boldsymbol{w}_{S-1}; \boldsymbol{b}_{S-1}, \boldsymbol{\theta}\Big).$$

Proof Log-likelihood - II

We apply Bayes rules to the left :

$$\mathbb{P}\Big(\boldsymbol{a}_{2:(S-1)}, \boldsymbol{w}_{1:(S-2)}; \boldsymbol{b}_{1:(S-1)}, \boldsymbol{\theta}\Big) = \mathbb{P}\Big(\underbrace{\boldsymbol{a}_{S-1}}_{\text{Station S-1}} \Big| \underbrace{\boldsymbol{a}_{2:(S-2)}, \boldsymbol{w}_{1:(S-2)}}_{\text{Until station S-2}}; \boldsymbol{b}_{1:(S-2)}, \boldsymbol{\theta}\Big) \mathbb{P}\Big(\boldsymbol{a}_{2:(S-2)}, \boldsymbol{w}_{1:(S-2)}; \boldsymbol{b}_{1:(S-1)}, \boldsymbol{\theta}\Big).$$

Plug in the right term :

$$\mathbb{P}\Big(\boldsymbol{a}_{2:(S-1)}, \boldsymbol{w}_{1:(S-1)}; \boldsymbol{b}_{1:(S-1)}, \boldsymbol{\theta}\Big) = \mathbb{P}\Big(\underbrace{\boldsymbol{a}_{S-1}}_{\text{Station S-1}} \Big| \underbrace{\boldsymbol{a}_{2:(S-2)}, \boldsymbol{w}_{1:(S-2)}}_{\text{Until station S-2}}; \boldsymbol{b}_{1:(S-2)}, \boldsymbol{\theta}\Big) \times \mathbb{P}\Big(\boldsymbol{w}_{S-1}; \boldsymbol{b}_{1:(S-1)}, \boldsymbol{\theta}\Big) \times \mathbb{P}\Big(\boldsymbol{a}_{2:(S-2)}, \boldsymbol{w}_{1:(S-2)}; \boldsymbol{b}_{1:(S-1)}, \boldsymbol{\theta}\Big).$$

Proof Log-likelihood - III

Using load $\boldsymbol{\ell}_{s-1}$ at station s and hypothesis (A_{2a}) :

$$\mathbb{P}\left(\boldsymbol{a}_s \middle| \boldsymbol{w}_{1:(s-1)}; \boldsymbol{b}_{1:(s-1)}, \boldsymbol{\theta}\right) = \mathbb{P}\left(\boldsymbol{a}_s \middle| \boldsymbol{\ell}_{s-1}; \boldsymbol{\theta}\right).$$

With (A_{2c}), we obtain :

$$\mathbb{P}\left(\boldsymbol{a}_s \middle| \boldsymbol{\ell}_{s-1}; \boldsymbol{\theta}\right) = \prod_{i=1}^{I} \mathbb{P}\left(a_{s,i} \middle| \ell_{s-1,i}; \boldsymbol{\theta}\right).$$

To sum up :

$$\mathbb{P}\left(\boldsymbol{a}_{2:S}, \boldsymbol{w}_{1:(S-1)}; \boldsymbol{b}_{1:(S-1)}, \boldsymbol{\theta}\right) = \prod_{s=2}^{S} \left(\prod_{i=1}^{I} \mathbb{P}\left(a_{s,i} \middle| \ell_{s-1,i}; \boldsymbol{\theta}\right) \right) \mathbb{P}\left(\boldsymbol{w}_{s-1}; \boldsymbol{b}_{s-1}, \boldsymbol{\theta}\right)$$

Platform position strategies

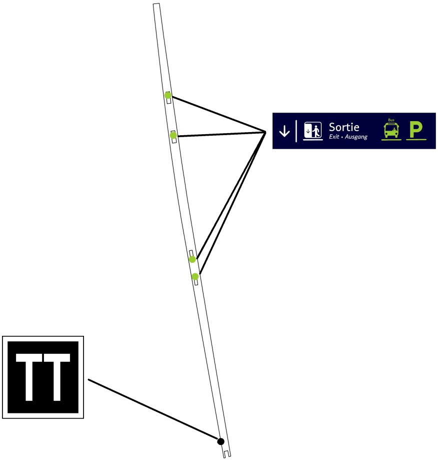
Strategic boarding passengers (SBP)
Minimize walking distance at departure

Strategic alighting passengers (SAP)
Minimize walking distance at destination

Departure station **Destination station**

Strategic confort passengers (SCP)
Travel in the least crowded car

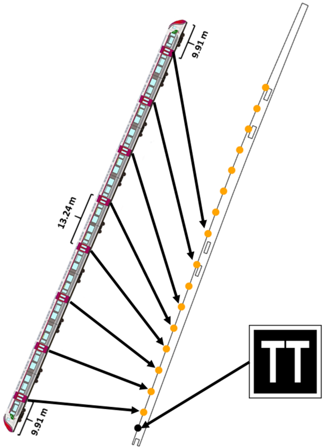
Platform main geographical elements



Geographical point : (2.345856, 48.9334)

1. Platform borders
2. J platform exits position, note ($E_{j,s}$)
3. Train stop point

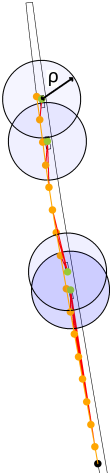
Train doors position



Space between doors : 13.24m or 9.91m

1. Deduce train doors position, note $V_{i,s}$ from train stop point
2. Make the hypothesis that train stop point is reliable

Exit attractiveness



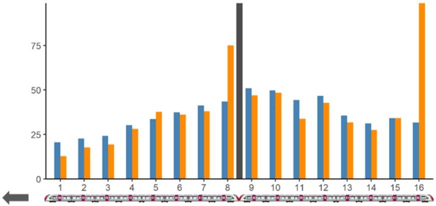
Exit attractiveness : ρ

1. Door i minimal distance to an exit :

$$d^*_{i,s} = \min_{j=1,\dots,J} d(V_{i,s}, E_{j,s})$$

2. Door i belong to an exit attractiveness area of radius ρ if $d^*_{i,s} \leq \rho$
3. One same exit attractiveness for all exits

Share of strategic alighting passengers (SAP)



Alighting distribution $(a_1, \ldots, a_I)$ and boarding distribution $(b_1, \ldots, b_I)$

The share of strategic alighting passengers is :

$$SAP_\rho = \frac{\sum_{i \in \mathcal{I}_\rho} a_i}{a_\bullet}, \qquad (2)$$

with $\mathcal{I}_\rho$ all the door's index which belong to an exit attractiveness area.

Bibliography I

[1] Francesco Corman and Pavle Kecman. Stochastic prediction of train delays in real-time using Bayesian networks. *Transportation Research Part C: Emerging Technologies*, 95:599–615, 2018.

[2] Sélim Cornet, Christine Buisson, François Ramond, Paul Bouvarel, and Joaquin Rodriguez. Methods for quantitative assessment of passenger flow influence on train dwell time in dense traffic areas. *Transportation Research Part C: Emerging Technologies*, 106:345–359, 2019.

[3] Rémi Coulaud and Martine Grangé. Modélisation de l'impact des flux voyageurs sur les temps d'échange pour la simulation des marges d'exploitation : une application à la ligne N de transilien. In *4èmes Rencontres Francophones Transport Mobilité (RFTM)*, 2022.

[4] Rémi Coulaud, Christine Keribin, and Gilles Stoltz. Quels modèles pour le temps de stationnement des trains en île de france? In *SFdS 2020-52èmes Journées de Statistiques de la Société Française de Statistiques*, 2020.

[5] Rémi Coulaud, Christine Keribin, and Gilles Stoltz. Modeling dwell time in a data-rich railway environment: with operations and passenger flows data. Re-submitted *Transportation Research Part C* (TRC) after corrections. Preprint accessible here `hal.archives-ouvertes.fr/hal-03651835/`, 2022.

[6] Rémi Coulaud, Christine Keribin, and Gilles Stoltz. One-station-ahead forecasting of dwell time, arrival delay and passenger flows on trains equipped with automatic passenger counting (apc) device. In *13th World Congress on Rail Research (WCRR)*, 2022.

[7] Rémi Coulaud, Valentine Mazon, Laura Sanchis, and Oded Cats. Share of strategic alighting passengers combining automatic passenger counting and OpenStreeMap. In *Conference on Advanced Systems in Public Transport (CASPT)*, 2022.

[8] Rémi Coulaud and Mathilde Vimont. How to use APC data to model passenger movement on-board? An application to Paris suburban train network. In *8th International Symposium On Transport Network Reliability (INSTR)*, 2021.

[9] Pavle Kecman and Rob M.P. Goverde. Predictive modelling of running and dwell times in railway traffic. *Public Transport*, 7(3):295–319, 2015.

[10] William H.K. Lam, C.Y. Cheung, and Y.F. Poon. A study of train dwelling time at the Hong Kong mass transit railway system. *Journal of Advanced Transportation*, 32(3):285–295, 1998.

Bibliography II

[11] Dewei Li, Winnie Daamen, and Rob M.P. Goverde. Estimation of train dwell time at short stops based on track occupation event data: a study at a Dutch railway station. *Journal of Advanced Transportation*, 50(5):877–896, 2016.

[12] Giorgio Medeossi and Andrew Nash. Reducing delays on high-density railway lines: London–Shenfield case study. *Transportation Research Record*, 2674(7):193–205, 2020.

[13] Carl-William Palmqvist, Norio Tomii, and Yasufumi Ochiai. Explaining dwell time delays with passenger counts for some commuter trains in Stockholm and Tokyo. *Journal of Rail Transport Planning & Management*, 14:100189, 2020.

[14] Timothy Pedersen, Thomas Nygreen, and Anders Lindfeldt. Analysis of temporal factors influencing minimum dwell time distributions. *WIT Transactions on the Built Environment*, 181:447–458, 2018.