Urban passenger transit modes are purported to achieve scale economies in passenger transportation, for both economic and environmental stakes. The larger and more populated the urban area, the more beneficial its transit network. The “passenger capacity” of a transit line establishes a hierarchy among the transit modes, from shuttle and bus lines to BRT, tramways and metros, up to train lines: the two basic factors being in-vehicle capacity and service frequency (TCQSM, 2013).

Transit operations and quality of service may be impeded by congestion under a variety of forms: in-vehicle passenger crowding is related to seat capacity and in-vehicle standing area, platform crowding depends on passenger arrival flows in relation to in-vehicle residual capacity and service frequency, railway track congestion involves vehicular flows in relation to track capacity that stems from its signaling system. These issues and the causal dependencies linking them are analyzed in (Leurent, 2011). They have been modeled in a variety of ways, principally in the theory of traffic assignment to transit networks (e.g. Gentile and Nöckel, 2016). Out of the congestion phenomena, passengers are especially appalled by the failure to board a dwelling vehicle that has no longer any space available to them. Then, a number of passengers fail to board the current vehicle and need to wait for the next one. Marcotte and Nguyen (2000) put forward a dynamic model of route diversion for the passenger flow in excess of the residual capacity provided by an incoming vehicle. Schmöcker et al. (2006) introduced the notion of Fail-to-Board (F2B) probability and embedded it in a static traffic assignment model. Further refinements are described in (Gentile and Nöckel, chapter 6).

To the service user, the primary consequence of F2B is to increase his wait time and make it less comfortable: as the platform is more crowded, he has to queue to maintain his order among the developing crowd of candidates. In the static model of Schmöcker et al (2006), “mingled waiting” is postulated to derive the average wait time from service frequency and F2B in a simple form. In fact, an F2B probability pertains to a vehicle as a whole: in a dynamic model n F2B probability can be associated to the i-th vehicle run serving station r, whereas in a static model the F2B is averaged over the vehicle runs that serve the station during a given period – despite the variations in vehicle headways as well as in passenger arrival flows.

Having defined the F2B in traffic physics and modeled it as a dependent yet simple traffic variable, a companion issue is to measure it on the field. The stake is twofold: firstly, F2B per se stands as an indicator of service congestion; secondly, the measurement of successive F2B values will enable one to estimate the distribution of passenger wait times, as a component of trip travel time hence as a quality-of-service indicator. The obvious method to measure F2B would be to monitor the number of waiting passengers on a platform and the number that are able to board in the successive vehicle runs. Denoting as N the number of waiting passengers at the instant of door closure and B that of passengers able to board, F2B can be estimated as N/(B+N) for that vehicle at that station.

While the monitoring of (N,B) pairs is an easy task for buses with one boarding door only and limited numbers of passengers, it would be much more difficult for trams, metros and trains that involve several doors and large to very large passenger flows. Boarding flows may be measured by devices (surveyors or sensors) at every door d, yielding flows B_ird to be aggregated over the doors to constitute B_ir. The measurement of N_ir is best achieved using a monitoring system made up of cameras covering the platform area and image processing algorithms.

Zhu et al. (2017) put forward an indirect method to measure boarding probabilities and the resulting wait times, by devising a probabilistic model of passenger travel time from an entry gate to an exit gate in relation to train passage times at the stations of interest. Their physical model involves an F2B probability at each station along a simple transit route. This probability is assumed constant for all train runs during a certain period. It is obtained by Bayesian analysis of individual tap-in and tap-out pairs of AFC data for users making that trip during the period.

Here our aim is to put forward a model both physical and stochastic of individual passenger travel times between gates along a railway line served by train runs possibly with insufficient vehicle capacity. F2B probabilities are modeled per train run and station along it. The combination of AFC and AVL data, for a given period of operations, enables one to estimate the F2B probabilities.

Our model builds upon that of Leurent and Xie (2017, 2018) to encompass F2B probability as well as in-station pedestrian distances and individual walk speeds, both of which are modeled as random variables. Based on the resulting probabilistic model of individual travel time, we express the probability density function (PDF) of a user exit time conditionally to his entry time. Given a set of observations, the PDF makes up a likelihood function of model parameters, among which the F2B probabilities. It can then be used for Maximum Likelihood Estimation (MLE) of any subset of parameters. To demonstrate the MLE, it is applied to study the case of RER line A in Paris on the morning peak of a working day of March 2017.

Let us quote some results:

1/ off-peak, train runs with positive F2B are very rare.

2/ on the morning peak (from 7:30 to 9:30 am) about 1 train out of 4 has significantly positive F2B.

3/ boarding saturation also occurs at the evening peak (from 16:30 to 19:30) in a less frequent way.

4/ at peak periods, boarding saturation occurred as an isolated event for one train only. We did not find sequences of 2+ saturated trains.

The body of the paper is organized in five sections. First, we introduce the physical model of the transit line in terms of service routes and station, along with service runs and passenger trips between stations (Section 2). Then, we make the model stochastic in order to capture variability or randomness in some variables as well as in the boarding process (Section 3). Next, we devise the MLE method on the basis of AFC and AVL data: particular specifications are introduced to ease computation (Section 4). Lastly, we study the case of regional train line RER A in Paris, arguably the busiest one in Europe (Section 5). To conclude, we sum up and point out to directions for further research (Section 6).