# Stochastic Passenger Flow Prediction in Large Train Networks 

Felix Gündling ${ }^{1}$ and Pablo Hoch ${ }^{1}$

${ }^{1}$ Technical University of Darmstadt


#### Abstract

We study the stochastic prediction of passenger flows in large train networks. Especially in scenarios that include disturbances and disruptions of train operations, passengers might end up in different trains than planned. We introduce a stochastic passenger behavior model that provides a probability for each real-time alternative in case of a broken connection. Each alternative is tracked from there on. This way, the model is able to predict a occupancy distribution for each train section. Our study on data provided by Deutsche Bahn Fernverkehr AG shows that our approach provides very high performance and is even applicable to real-time scenarios to support dispatchers by providing information about passenger flows in real-time.


Keywords: passenger flow, prediction, stochastic, train

## 1 Introduction

Passengers using public transport typically plan a journey in advance. However, because of delays or train cancellations, they may miss an interchange or a train they planned to use doesn't operate on the day of their journey. In these cases, passengers switch to alternative journeys to reach their destination, which can cause the capacity of alternative trains to be exceeded.

Our goals are the detection of broken journeys caused by delays, train cancellations, and route changes, predicting which alternative journeys passengers are likely to use and to create a forecast for the expected number of passengers for each travel section
of a train. This allows operators to identify possible capacity shortages. We use an interchangeable passenger behaviour model which rates alternative journeys based on criteria such as travel time and number of transfers and calculates a probability of choice for each alternative. Our model tracks all possible route choices with the associated probabilities. The load forecast is calculated as a probability distribution.

Previous approaches $[1,2,3,4,5,6]$ only use a weighted sum of travel time and the number of interchanges to determine the journey taken by the traveler.

## 2 Methods

The main data structure is a directed graph, which is based on a time-expanded graph of the timetable. The nodes are departure and arrival events of trains. For each node, we store two timestamps - the time according to the schedule and a real-time based on delay reports and predictions - as well as a flag indicating if that event has been cancelled. Travel edges connect departure events of a train to the next arrival event of that train and wait edges from arrival to departure events of the same train at the same station model the time spent at a station.

To track passenger groups, for each travel and interchange edge we store a list of passenger groups using that edge. Passenger groups are added to all edges of their planned journey and interchange edges are added to the graph where needed. We add an additional interchange edge from the start node to the departure node of the first train used in the planned journey, and an interchange edge from the arrival node at the destination to the destination node. These additional interchange edges allow us to detect broken journeys if the departure at the start or the arrival at the destination are cancelled. For each travel edge where such information is available, we also store the capacity of the train on that section. Each passenger group also has an associated probability, which is initially 1 for all planned journeys, that determines how likely it is that this group is traveling on its associated journey.

We receive real-time delay, cancellation, and rerouting updates. The graph is updated to reflect these changes. Whenever a node is modified, we check all interchanges on incoming and outgoing edges to see if they are now broken.

Once the broken interchanges have been identified, we search for alternative journeys for the affected passenger groups that allow them to reach their destination. First, we identify where each affected passenger group is located at. We then calculate alternatives to their planned destination and use a behaviour model to determine a probability of choice for each alternative. The behaviour model is interchangeable; models such as discrete choice models can be used.

Since each passenger group has an associated probability, the number of passengers in a train section is not a single number, but a probability distribution which can be
calculated using convolution. This allows the detection of sections where the capacity is exceeded with a given probability.

## 3 Results

We tested our implementation with a timetable and real-time updates (delays, train cancellations, route changes and additional trains) for Germany and planned journeys for a single day. There were 538,783 passengers, from which we created 372,283 passenger groups.

For evaluation purposes, we applied the real-time updates in a batch mode in oneminute intervals, i.e., 1440 updates. Simulating the whole day, i.e., applying the realtime updates, detecting broken journeys, calculating alternative journeys and updating the tracked passenger groups with alternative routes, takes 30 minutes. The longest update took 78 seconds; however most updates took much less than 60 seconds, meaning that the system can be used in real-time most of the time.

Figure 1 shows an example load forecast for a train with 7 sections (x axis) and a capacity of 430 (y axis). The dotted black line shows the planned number of passengers, and the blue area shows the expected passenger range according to our forecast after real-time updates have been applied. The dark blue line shows the median value of the forecast and the percentage numbers at the top of the graph indicate the probability that the capacity of a section is exceeded.


Figure 1: Example train load forecast

## 4 Conclusions and Contributions

In this study we presented a scalable approach for tracking a large set of passenger journeys in real-time. The behavior model provides a probabiliy for each real-time alternative in case the original journey is not feasible anymore due delays, cancelled stops, etc. This further increases the number of journeys that need to be tracked by the system. Using this approach, the dispatchers are provided with a occupation probability distribution for each segment. Our evaluation on data provided by Deutsche Bahn Fernverkehr has shown that the approach presented here is capable of providing real-time information about all tracked passengers.

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