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D3.2: Algorithms for short-term prediction of passenger flows

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TRANS-FORM

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1. Summary

Public transport networks are increasingly complex and multimodal and thus challenging to manage, while it is increasingly important that the networks are robust (Törnquist Krasemann 2012). One of the goals of this project, TRANS-FORM, is to develop effective strategies and methods to support decision makers in transforming public transportation into a seamless travel experience perceived well by the travellers. Furthermore, the project focuses on the development of an integrated passenger-oriented management approach that takes advantage of multiple data sources and state-of-the-art scheduling support. The “passenger-oriented” means that the planning and operational control of the public transport service network do not only concern operator- and network-related aspects, but also considers the reliability of passenger transfers and quality of service. In order to introduce and apply effective passenger-oriented control and management strategies, predictions of the passenger flow dynamics - including passenger route choice estimations due to real-time re-scheduling of services - could be useful.

This document reports the work performed in task 3.3 entitled “Short-term forecasts of passenger flows” as a part of work package 3 “Methods for planning and operating robust services” of the TRANS-FORM project.

The work in the above-mentioned task focuses on how to predict short-term demand, as an effect of changes in the transport service network due to e.g. disturbances and passenger preferences. This document presents the algorithms for passenger flow predictions to be incorporated in the real-time management strategies for the three different levels (hub, urban and regional) that are outlined in the previous project deliverable “D3.1: A toolbox of real-time strategies for smart transfers”.

2. Introduction

As written in the previous deliverable, D3.1, this work package 3 focuses on how to develop an integrated passenger-oriented management approach that enable improved coordination and smooth passenger transfers. In the previous tasks 3.1 and 3.2, real-time management strategies of the three different levels (hub, urban and regional) have been developed, and the model integration was discussed. The focus of task 3.3 is on developing algorithms for short-term forecasting of passenger demand, which underly the real-time passenger-oriented strategies.

Since the “real-time” strategies are executed to control passenger flows and achieve the smooth transfers based on the evolving states of the system, the prediction should be conducted at high temporal resolutions. The short-term prediction algorithm is developed for this purpose, i.e., to predict the change of passenger flow in reaction to the controls that have already been executed by the current time step, which helps the decision of the current and future strategies. In the field of transportation research, such algorithms have attracted a lot of attention and been developed especially in the application of Intelligent Transportation Systems (ITS), as the direct result of an increasing need for developing user friendly services and phenomenal technological and computational advances (Vlahogianni et al., 2004; 2014).

Figure 1 shows how the short-term prediction algorithm is used in a real-time management strategy. The red line is the reference trajectory to be achieved. At the current time step, based on the measured output (orange line) in reaction to the past control input (blue line), the algorithm predicts the demand. This prediction is used to decide the controls (green line) in the several next times, so that the system state goes close to the reference trajectory (red line). Thus, the management strategy is adjusted in real-time based on the short-term prediction algorithm.

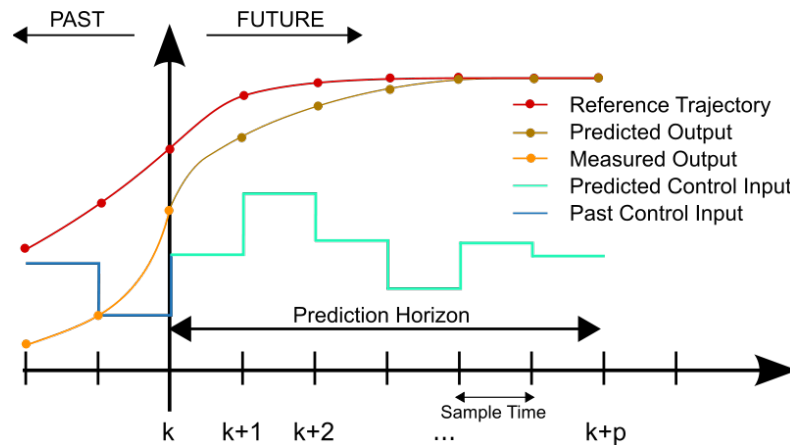


Figure 1: Image of short-term prediction, created by Martin Behrendt and cited from https://commons.wikimedia.org/wiki/File%3AMPC_scheme_basic.svg

This deliverable is structured as follows. Section 3 introduces the prediction algorithms of the different three levels, i.e., hub, urban and regional levels. Each subsection in Section 3 corresponds to the algorithm at each level and explains how it works with the overview figure of the algorithm. Section 4 concludes this deliverable. The list of references is provided in Section 5.

3. Prediction algorithms

3.1. Hub level

Predicting short term passenger flows inside the hub is a matter of minutes and even seconds in some cases, i.e., the pedestrian flows are evolving rapidly in an unpredictable manner. As seen in the previous deliverables, vary high temporal and spatial variations take place. Therefore, to be able to forecast in some way these flows, the time steps must be sufficiently small in order to capture these variations. The horizon considered in the short-term prediction is usually minutes with time steps of the order of seconds.

The objective of the prediction of short-term passenger flows is to provide information to the controller on the future state of the system. This way, the controller can take decisions while having some insight on the future state of the system. This is important for the hub model that the strong variations in pedestrian flows induced by trains can drastically change the level-of-service in the hub, such as the congestion level, walking speed and time, within a few seconds.

To accomplish this, many different factors can be taken into account into a prediction algorithm. One of the most significant factors is the timetable. The arrivals and departures of PT vehicles (trains, buses, trams, etc.) induce the main pedestrian (passenger) flows inside the hub. Another important element which can be used to facilitate predictions is the analysis of recurrent patterns. As project deliverable D1.2 showed, recurrent patterns take place within weeks, days or even hours. Other factors like weather or special events (concerts, football games, etc.) can also provide valuable information for predicting passenger flows.

3.1.1. Algorithms

The short-term prediction algorithm at the hub level consists of the pedestrian simulator, the use of historical data and public transport induced flows. Historical data gives the aggregated demand inside the hub and is updated by the induced flows based on the time-table of public transport. The aggregated demand is then used as the input for the pedestrian simulator, which includes both the pedestrian movement model and the activity scheduling model, and thus the level-of-service inside the hub is evaluated. This information is the key metrics for the controller, and the strategies in the next time steps are decided in real-time.

Using patterns

Historical data can be collected and processed in order to emphasize the patterns which take place. The patterns that are interesting for the hub model are the number of passengers alighting and boarding public transport vehicles and the inflow and outflow from the infrastructure. Insights into these patterns can be acquired using link flow counts. The average of those values can be computed and then used as input for simulations.

Using public transport induced flows

When a train arrives at a platform and the doors of the carriages open, all the passengers wishing to disembark will start exiting the train and becoming pedestrians inside the hub. This is true for any public transport mode, here the train is used as an example. This flow induced by the train can be predicted as most of the information characterising the flow is known before the train arrives. The number of passengers who want to disembark and the platform where the train arrives can be acquired relatively easily. The more challenging piece of information is the destination of each passenger. Nevertheless, studies analysing the activity scheduling of individuals can address this issue by providing information, at an aggregate level, specifying the next destination of passengers. For example, for the station in Lausanne the fraction of passengers taking buses, the metro, and walking are known. Thanks to all these elements, the flows of pedestrians can be predicted. In order to simplify the model, a constant arrival rate into the infrastructure from the train is assumed. For more information about this process, see (Molyneaux, N., Hänseler, F. S., & Bierlaire, M. 2014).

Flows of passengers heading towards trains (boarding flows) can also be estimated based on the timetable. Pedestrians are “attracted” to the platforms as they wish to take the train which is leaving from that specific platform. Although the flow rate is not as high, accurate modelling of these flows is just as important. One common approach for modelling arrival rates of pedestrians is the Poisson process.

Pedestrian simulator

Using the aggregate demand given by the historical data sources and public transport induced flows, the pedestrian simulator conducts an agent-based simulation of pedestrian behaviour inside the hub. The simulator consists of two main models; an activity-scheduling model and a pedestrian movement model. The activity-scheduling model predicts the choices of activity locations and routes of pedestrians with temporal information, given the aggregate demand. Based on the output of the activity-scheduling model, the pedestrian movement model predicts more microscopic pedestrian movements in the hub as the sequences of x-y-t coordinates.

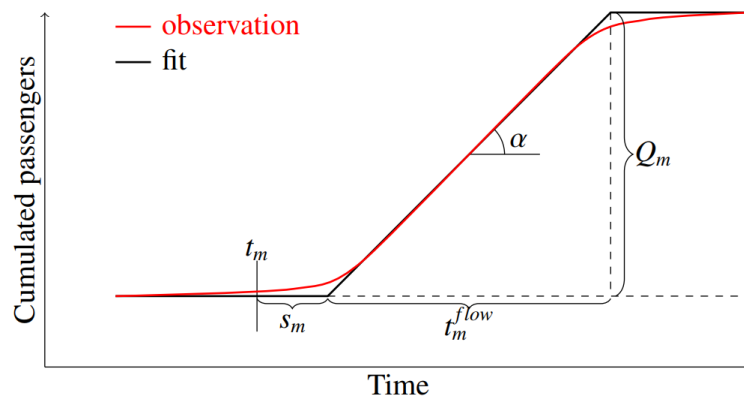


Figure 3 Piecewise linear specification of the model for alighting passengers. A constant arrival rate is used to model the arrival of pedestrians into the infrastructure.

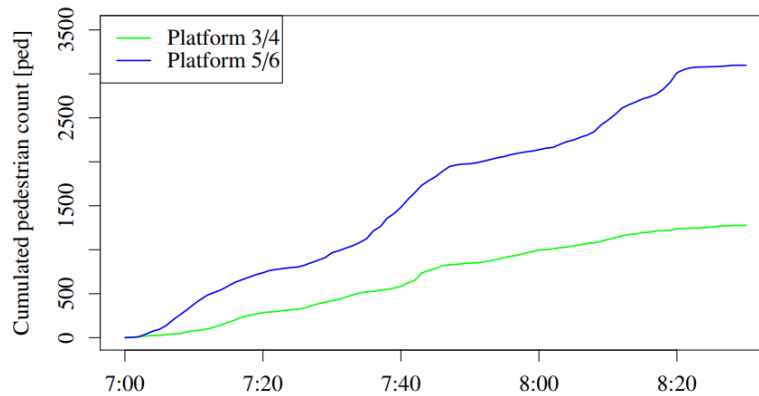


Figure 2 The empirical data of pedestrians arriving onto two different platforms. No distinct process is visible, hence a Poisson process is considered for modelling the entrance of pedestrians into the station.

3.1.2. Utilization by the controller

As described in previous deliverables, the objective of the controller is to take decisions in order to improve the flow dynamics. Regardless of the decision variables which are available, the controller will use estimations of the state of the system and try to take the “best” decision at a given time. To improve the decision-making process, the controller can use information not only for the current and past time intervals, but also predictions of the future time intervals. The controller will perform a simulation of the next couple of time steps in order to

acquire information on the upcoming events. Then, based on this information the optimal control strategies will be taken and implemented for the current time step. This rolling horizon procedure is repeated throughout the simulation.

Short term prediction overview

Figure 4 presents an overview of the interactions between the different components taking place in the short-term prediction algorithm at the hub level. The objective is to predict the future state of the network by using different algorithms at disposal. Three elements can be used to predict the future state of the system. Historical data, the PT schedule or by simulation. The latter requires as input the current state of the system. The output from these three figures is combined into the “future state prediction”. The control algorithm which takes decisions can then use both the current network state and the future network state to take the best possible decision at that time. This procedure is applied in a rolling horizon manner to all future time steps.

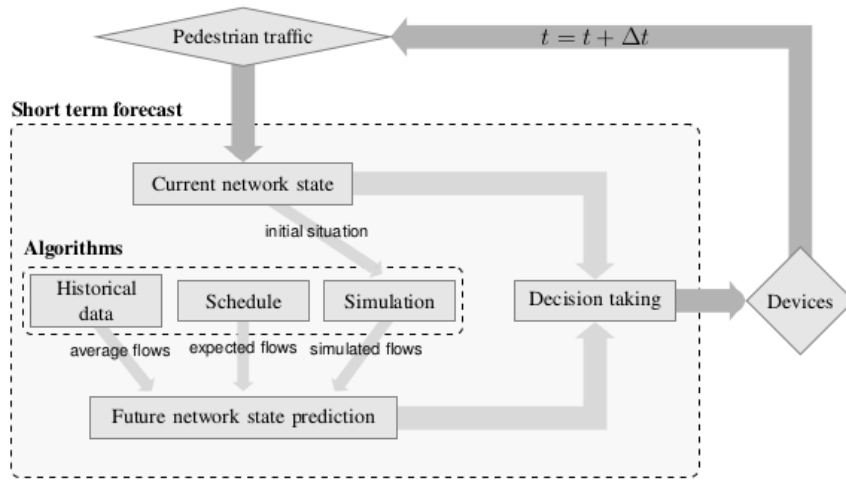


Figure 4: General overview of the interactions between the different components of the short-term prediction used at the hub level.

3.2. Urban level

3.2.1. Prediction time step

For the urban public transport (PT) network level the goal of the control algorithm is to determine whether to apply holding to urban PT services at the multi-level transfer stop s_t , in order to provide a connection for certain single-level and/or multi-level transferring passenger. The decision whether to hold a certain urban PT service for a certain holding time t^h at s_t is based on the quantification of the predicted impact of this holding strategy on the different passenger groups affected by this decision. By subtracting predicted passenger group costs from predicted passenger group benefits inflicted by the holding strategy, the controller determines the holding time of run r . The objective of the controller is to maximize the net effect of holding time on passengers.

The holding time value can theoretically range between 0 seconds and the headway h_r between the considered run r and subsequent run r^+ . For the controller to be able to execute this decision, the impact of this decision on the different passenger groups needs to be predicted. To quantify these passenger effects, this means that for each of the variables mentioned in the formulas in section 3.2 of WP3.1, a (deterministic or stochastic) value needs to be predicted either based on historical data or based on real-time information. In the case that values are predicted based on real-time information, the required time interval for this information to be updated will be seconds or partial minutes (e.g. every 10/20/30 seconds). This is necessary for the controller to be able to update the decision whether / how long to hold an urban PT service adequately. The range for the control decision variable t^h will be between 0 and about h_r . For the case study of a urban controller application for

high-frequent urban public transport services, this means the total solution space for t^h is expected to contain several minutes in most of the cases, depending on the exact frequency of the urban PT service. A time step per minute is too rough given this solution space: it is therefore necessary to consider time steps of parts of minutes, or seconds.

3.2.2. Prediction of variables

This section refers to all formulas provided in section 3.2 of WP3.1, used to quantify the impact of the applied holding strategy. For all variables of each formula, it is discussed how the value can be obtained. For explanation regarding the notations used in the formulas, the reader is referred to section 3.2 of WP3.1.

Number of boarding and alighting passengers

The number of boarding passengers $q_{r,s}^{in}$ generated at each stop – non-transferring passengers – is calculated using formula (1) and is equal to the passenger arrival rate λ_s multiplied by the headway h_{r-} between previous run r^- and run r .

$$q_{r,s}^{in} = \lambda_s \cdot h_{r-} \quad (1)$$

The holding time t^h directly affects the headway between services. The (time-dependent) passenger arrival rate is estimated from historical AFC (Automated Fare Collection) data. Based on individual AFC transactions and applying a transfer inference algorithm, an OD matrix is inferred for a specific time period (e.g. per (half) hour). Based on historical AFC data and long-term travel patterns, an (e.g.) hourly OD matrix can be estimated for each specific time and day. Passenger demand d_{ij} between a certain origin stop i and destination stop j is hereby a function of (amongst others):

- Time of the day;
- Day of the week;
- Month of the year;
- Holiday / no holiday; and
- Special events.

Under the assumption that the passenger demand is uniformly distributed within the considered time for which the OD matrix has been estimated (based on historical AFC data and the abovementioned time-related characteristics), the passenger arrival rate can be calculated. Given the high-frequency context, passengers are assumed to arrive at random rate at the stop. Hence, the arrival rate equals the total demand between origin stop s and all destinations j divided by the total time period τ .

$$\lambda_s = \frac{\sum_{j \in J} d_{sj}}{\tau} \quad (2)$$

The number of alighting passengers $q_{r,s}^{out}$ then results from the historically predicted demand d_{ij} and the number of passengers boarding a certain run $q_{r,s}^{in}$ at all stops of the line upstream of the considered stop. Formula (3) shows that the predicted number of alighting passengers $q_{r,j}^{out}$ from run r at each intermediate or last stop of the line j equals the number of boarding passengers from all stops s of run r upstream of j alighting at j .

$$q_{r,j}^{out} = \sum_{s=1}^{s-1} q_{rs}^{in} \quad (3)$$

Arrival and departure times

To predict the impact of holding, the arrival and departure times of runs need to be predicted as well. Automated Vehicle Location (AVL) and GPS data provide real-time information about the position of each run. In order to predict arrival and departure times at a certain stop, real-time position information is combined with model predictions of the running and dwell time. If no other data source is available, expected running and dwell

times can be obtained from the schedule. Scheduled running and dwell time are then directly used to predict the arrival and departure time at/from each downstream station, given the real-time position of a certain vehicle. This prediction scheme is widely used in practice and performs relatively well (Cats and Loutos 2016a, 2016b). This prediction scheme is already available in the urban PT simulation model, BusMezzo. Alternative prediction schemes can also be implemented either internally or using an API.

The prediction of arrival and departure times on the urban PT network level takes place within the urban PT model. To predict holding impacts for a multi-level PT network, predicted arrival and departure times of services on the (inter)regional PT network level at multi-level transfer locations are also required. The predicted arrival times of (inter)regional PT services at the multi-level hub are obtained from the (inter)regional train model. Section 3.3 discusses how these values are obtained.

Passenger transfers

To predict the number of transferring passengers from the (inter)urban train network (multi-level transfers) or the urban PT network (single-level transfers) to the urban PT network at a transfer stop, formula (4) is applied. In case of multi-level transfers from the (inter)urban train network, the (inter)regional train model provides a prediction of the number of alighting train passengers at the multi-level stop, as well as the predicted arrival platform of the (inter)regional train service. Section 3.3 provides information how these values are predicted. In case of single-level urban network level transfers, the number of alighting passengers from an inbound urban PT run is predicted using formula (3). $f_{r_o|q_{r_i s t}^{out}}$, the fraction of alighting passengers from an inbound PT service aiming to transfer to a certain urban run r , is determined based on historical data. Historical AFC data and – specifically for the case study of The Hague – percentages based on integration of regional (NS) and urban (HTM) AFC data are used to determine this fraction. This allows the prediction of this value for both single-level and multi-level transfers to the urban network. Based on the time period of the day, day of the week and season, this fraction is predicted from the historically available data. $f_{r_o|q_{r_o r_i s t}^{out}}$ is the fraction of transferring passengers from a certain inbound PT service to a certain outbound urban PT service, which makes this connection. This value is predicted, based on the predicted transfer walking time. The transfer walking distribution between each interurban PT platform and each urban PT platform, and between all urban PT platforms, is obtained from the hub level model, and can be specified for different periods of the day if crowding affects the distribution function. In the control decision, $f_{r_o|q_{r_o r_i s t}^{out}}$ for a certain departure time of the urban PT service is predicted based on a probabilistic function using the expected value of the transfer walking time distribution, the predicted arrival time of the (inter)urban inbound PT service and thus the available transfer time.

$$q_{r_i r_o s t}^{trans} = q_{r_i s}^{out} \cdot f_{r_o|q_{r_i s t}^{out}} \cdot f_{r_o|q_{r_o r_i s t}^{out}} \quad (4)$$

Occupancies

Occupancies for each run on each segment can be calculated based on the predicted number of boarding, transferring and alighting passengers at stops upstream of the considered link segment, see formula (5). Based on vehicle specifications regarding the seat capacity φ_r^s , crush capacity φ_r^c and surface available for standing passengers θ_r^c for each vehicle type of a run, the crowding seat capacity in-vehicle time multiplier γ_s and the crowding standing density in-vehicle time multiplier γ_d can be determined using formula (6) and (7).

$$q_{rs} = \sum_{s=1}^s q_{r,s}^{in} + \sum_{s=1}^s \sum_{r_i \in R_i} q_{r_i r_o}^{trans} - \sum_{s=2}^s q_{r,s}^{out} \quad (5)$$

$$\gamma_s = \min\left(\frac{q_{rs}}{\varphi_r^s}, 1\right) * \beta_5 \quad (6)$$

$$\gamma_d = \max\left(\frac{q_{rs} - \varphi_r^s}{\theta_r^c}, 0\right) * \beta_6 \quad (7)$$

Short-term prediction overview

The figure below summarizes the information input and output for the short-term passenger prediction algorithm used for the urban network level. Based on the spatial passenger distribution of the network, a current state is obtained regarding passenger flows. The future state, the predicted passenger flows, is the result of both historical and realized / simulated data in relation to passengers and vehicles. Based on historical demand data and realized passenger counts, the passenger arrival times, destinations and fraction of transferring passengers are obtained. Vehicle positions at a certain time instance result from the timetable (scheduled departure and arrival times for each run and station) and from real-time or simulated data (realized departure and arrival times). Based on the current state and future short-term passenger flow predictions, a control decision can be taken by the controller, resulting in a new spatial passenger distribution over the network.

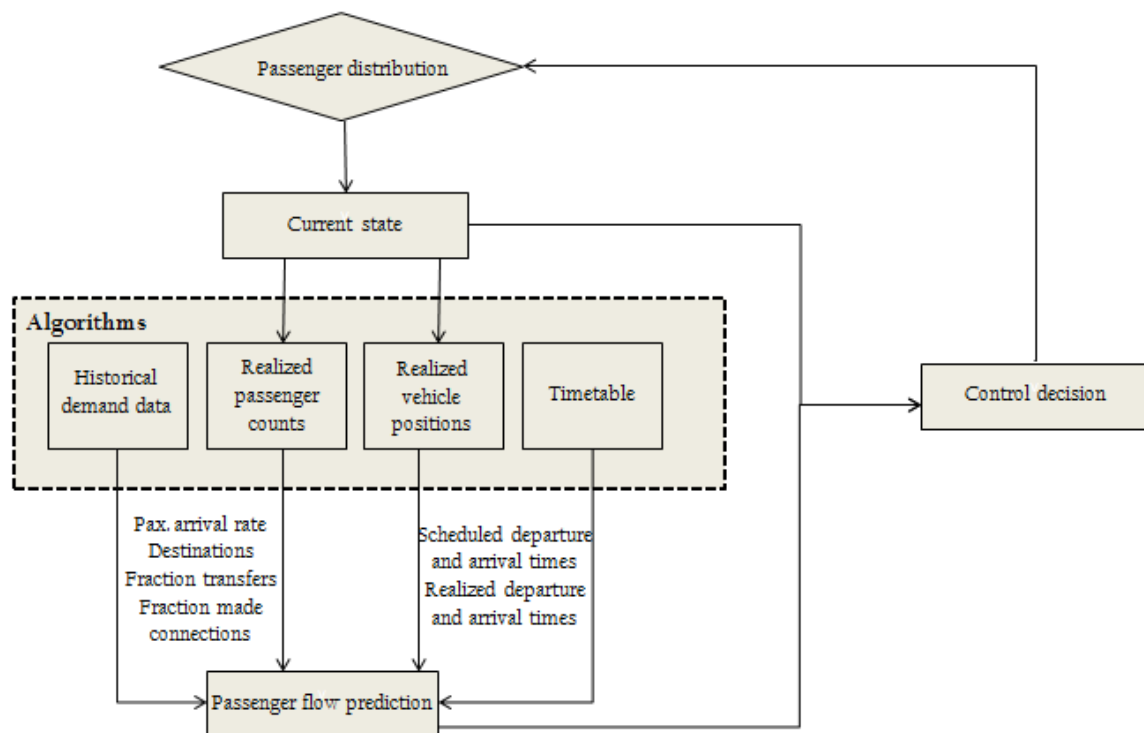


Figure 5. Information flow for short-term prediction algorithm urban network level

3.3. Regional level

The short-term prediction of passenger flow for the regional level consists of two steps, 1) the generation of a demand profile, and 2) the demand flow propagation and train optimization. The first step is based on historical data, and the second step takes the demand profile, together with information about the planned time table and information about the disturbance that affect the train operation, as input. The section first describes the historical demand profile input data, followed by a description of how the train optimization will produce an update to the demand (updated demand) as a result of optimal train re-ordering given the disturbance.

3.3.1. Demand profile generation

Regional train and long-distance bus trips are normally planned by the traveller in advance, sometimes by purchasing a ticket for a specific departure time and destination in advance. Other travellers normally have a specific destination and departure time in mind when arriving at the train or bus station. In both cases, the trip is planned based on the currently available time table for the services.

When train tickets are bought in advance it is, in theory, possible to know the destination stop in advance. However, for the case where most of the trips are paid using monthly cards, this is not the case. Furthermore, the number of passengers is known only once they tap in on the specific train or bus. The tap in gives no specific information about the final destination. Information about the sequence of stops of the vehicle boarded is known, but not where the final destination is, or if the traveller plan to transfer to another vehicle before arriving at the final stop. This implies that the exact knowledge of both the origin and destination of the travellers can be known only after that the trip is completed. This, in turn, implies that the distribution, and transfers, of the travellers needs to be estimated based on historical data.

The timetable for the trains and the busses are identical for each weekday, but different for the weekends. However, the travel demand pattern is typically different for different days of the week. Thus, the historical demand profile is an aggregated demand profile computed separately for the three group of days, Monday to Thursday, Friday, and Saturday to Sunday. The estimated demand profile for each group will cover 24 hours and will be based on one month of processed tap-in data.

An example of a demand profile for passengers only travelling on one of 10 train departures in the Monday to Thursday group, is visualized in Figure 6. The figure shows the distribution of passengers boarding trains at the Karlskrona station, on a Krösatåg, travelling north where the final destination of the train is Emmaboda. The widths of the lines between the stops are drawn proportional to the number of passengers. From the figure, we note that the number of passengers travelling on this route in the morning is lower than the number of travellers in the evening. In this example, no traveller has a destination at any other stop than at, Bergåsa, Holmsjö, Vissefjärda or Emmaboda. In other cases, the destination may not be along a specific train line, and the passenger transfer at one stop and continue on another line. The information about transfers is derived from the tap-in data.

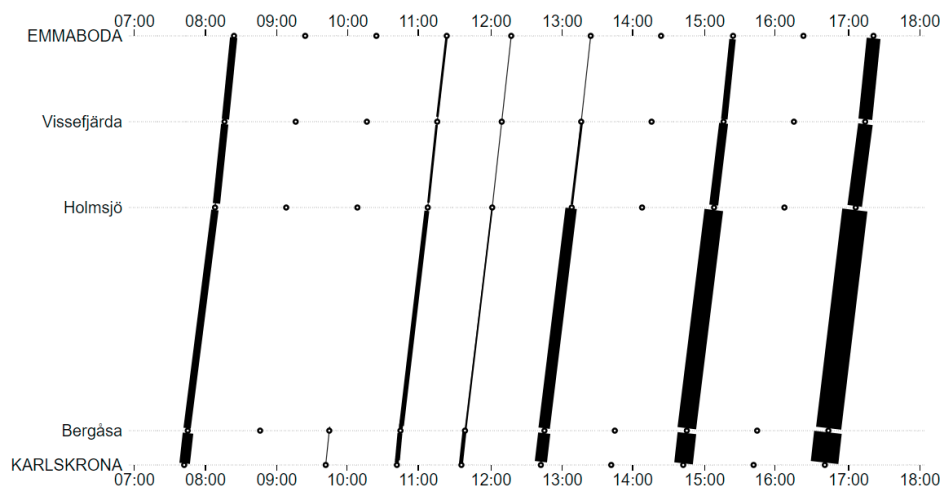


Figure 6: A graphical timetable that shows the number of passengers from Karlskrona station towards Emmaboda station for 10 train departures. The widths of the lines are proportional to the number of passengers. The horizontal axis shows time of day, and the vertical axis indicates the location (name of station).

With the basis that the travellers are assumed to have planned the trip in advance, and the fact that the optimization process will be applied to minor disruptions (disturbances), we assume that all travellers in the forecasted situation will arrive at the departure stop, and distribute on the final destinations, with the same pattern as for historical days. Here, we will predict both the number of travellers, the boarding stop time and stop and the distribution of their final destinations, based on historical data. In practice, in case of special events, when the number of passengers is higher or lower than usual, the estimation of the number of

passengers may be updated, but the distribution on the different destination cannot. The predicted origin demand will be given on the level of departure vehicle and passenger group $g \in G$, where a group of passengers is defined by the transfers made. All passengers with the same transfer, and therefore the same route, will define one group, passengers using different routes will be in different groups. That is, for each group of passengers, a set of routes, denoted R_g , from the origin to the destination is defined. Since the end point of the trip, outside of the public transport system, is unknown, the destinations will be specified on the city/village level only. The motive for this is that when using, for example, a replacement bus, the stop of this bus might not be at the exact same stop as the planned train, although for most train destinations a bus stop is available close to the train station.

3.3.2. Optimization of trains using the demand profiles as input

The demand profile is input to the timetable optimization problem. The regional level train sequencing and scheduling optimization model will be used to model minor disruptions, compared to the planned schedule. This means that train and bus re-ordering and holding strategies will be applied in order to minimize the effects of the disturbance for the passengers. No trains will be cancelled or added to the schedule; replacement buses will be offered only in specific cases. The objective used when finding the adjusted timetable is a weighted combination of train delays and passenger delays. The delays are measured as the arrival time difference between the scheduled time and the time given by the adjusted timetable for each vehicle and each passenger.

For the optimization model, a set of passenger groups G is defined. A passenger group $g \in G$ is characterized by the quadruplet (o_g, d_g, t_g, n_g) where o_g is the origin, d_g is the destination, and t_g is the departure time from the origin. The parameter n_g specifies the number of passengers. The data in the quadruplet is given by the demand profile. For each group of passengers, the model takes a set of routes, denoted R_g , from the origin to the destination. All passengers in the same group are assumed to follow the same path in the transport network, that is, they are kept together on the same vehicles throughout the route, in the model. The route chosen is updated inside the optimization process, based on the most efficient way (fastest path) to get to the destination, given the optimal re-ordering of the trains with respect to the updated route used.

The overall structure of the demand forecast and update process is illustrated in Figure 7. The optimization process, where the optimal train holding strategies and train sequences are found, will result in updated travel demand. Note that the update of the demand is only an update of the route, that is transfer locations and transfer times, and the arrival time at the final destination, the initial demand at the first stop is not updated in the optimization process. The updated travel data is the realized schedule for the trains, the realized transfers made by each of the passenger groups, and the arrival times for each of the traveller groups. No travellers are assumed to change the final destination (on the city/village level) during the trip. This demand update constitutes the short-term demand prediction produced by the simulation and optimal train re-ordering algorithm. The train schedule for the scenario is input data together with historical demand profiles for the travellers. The historical demand profiles consist of information about the boarding stops and boarding times (or, the times when the traveller will be present at the boarding stop, in the case of a disturbance that affect the travellers at the first stop) and the sequence of trains that were used by this demand. The sequence of used trains defines the planned transfer, which is an essential input for the simulation and optimal train re-ordering algorithm. Further, the simulation and optimization algorithm will take the disturbance scenario as input. The optimization process will provide information about the realized trips, that is, the reactions of the travellers to the disturbance in the train traffic, based on rational travellers with the aim of reaching the final destination as fast as possible.

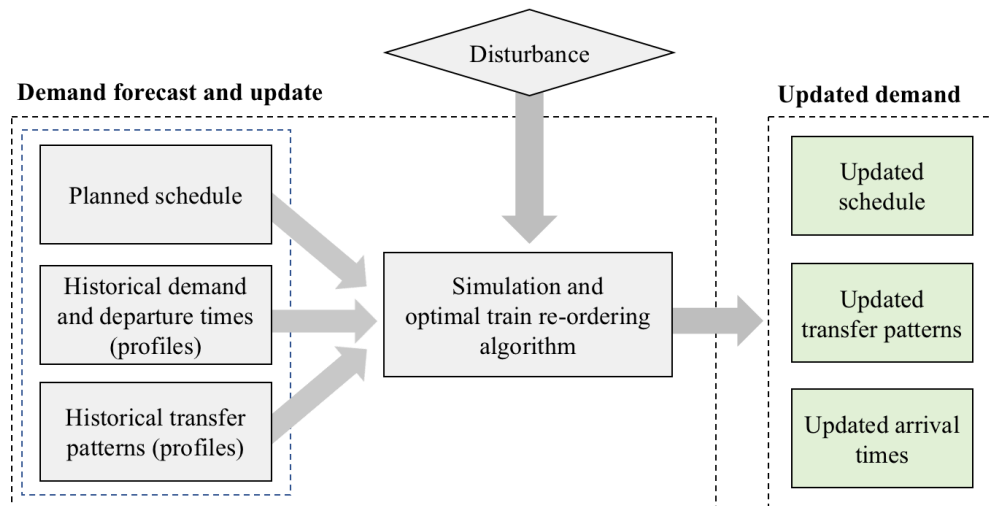


Figure 7: Demand forecast and demand update structure for the regional level.

4. Conclusions and Prospects

This document reports on the work of task 3.3 “Short-term forecasts of passenger flows”, which focuses on developing algorithms for short-term prediction of passenger flow, which underlie the real-time management strategies. These algorithms will be incorporated into the management strategies developed in task 3.1 and task 3.2 and applied to case studies in the following work package 4 entitled “Application and demonstration of smart transfer strategies”.

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