A two-step approach for estimating pedestrian demand in a congested network

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Abstract

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In the framework of PedFlux, a long-term research project jointly carried out by the Swiss Federal Railways (SBB) and EPFL, pedestrian flow patterns arising in complex train stations are investigated. For this purpose, a large number of visual, depth and infrared sensors have been installed in Lausanne railway station, covering two pedestrian underpasses and a train platform. Their information is processed by a human motion detection algorithm, which allows to locate and track pedestrians along their way through the train station.

A central goal of PedFlux is the development of a methodology for dynamically estimating pedestrian demand in train stations. Along these lines, a pedestrian cell transmission model (PedCTM) and a preliminary demand estimator taking advantage of the above-mentioned measurement data have been successfully developed. In this Bachelor’s thesis, a two-step approach for demand estimation is developed and implemented by building on these achievements. This approach is believed to be a reasonable approximation to the fixed-point arising from demand supply interaction in a mildly congested network. Moreover, a fixed-point solver is developed and the results are compared. To investigate the feasibility of the proposed methodology, a case study analysis of a part of Lausanne railway station and of a bottleneck experiment is performed.
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Chapter 1

Introduction

1.1 Introduction

Pedestrian flows in public walking areas, and in particular in transportation hubs, have a significant impact on safety, comfort and timetable stability. To better understand this influence, and to improve the level of service, we need a mathematical model.

This thesis presents a framework for dynamically estimating pedestrian demand in congested walking facilities. It combines a demand-inelastic demand estimator and a pedestrian flow model. An important part of the work done in this thesis is also the improvement and development of the demand estimator originally presented by Mazars-Simon, Q. (2014)

1.2 Literature review


Hänsele, F., Molyneaux, N., Bierlaire, M., Stathopoulos, A. [STRC, 2014]. Schedule-based estimation of pedestrian demand within a railway station, Transport and Mobility Laboratory, EPFL.

Chapter 2

Dynamic demand estimator for uncongested networks

2.1 Introduction

In order to develop the framework for this project, a demand estimator and a flow simulator are required. While the last (PedCTM) is available and fully working, only a simple version of the demand estimator is functioning. This work has helped to extend and improve this estimator. It is not the purpose of this thesis to fully describe the estimation framework as such, since this can be extensively found in Haenseler et al., 2014, but to introduce its main concepts and possibilities, and to analyze the results obtained when tested in Lausanne railway station.

In the context of origin-destination (OD) pedestrian demand estimation, different sources of information need to be available. These sources may include train timetables or direct measurements on the network such as link flow counts or pedestrian trajectory recordings. For solving the demand estimation problem, an assignment mapping that defines the temporal and spatial relationship between the origin-destination (OD) demand and these measurements is required. In absence of congestion, we can build this mapping based on a demand-inelastic supply model, i.e. a demand-inelastic walking model.

2.2 Model definition

The main concepts of the model used to estimate OD demand will be briefly described in this section. A more extensive description can be found in Haenseler et Al., 2014 and in Mazars-Simon, 2014.
2.2.1 Time and space representation

The period of analysis is divided into a set of discrete time intervals $\mathcal{T}$, where each time interval $\tau \in \mathcal{T}$ is of uniform length $\Delta t$. The network of pedestrian facilities is represented by a directed graph $G = (\mathcal{N}, \mathcal{L})$, where $\mathcal{N}$ represents the set of nodes $v \in \mathcal{N}$ and $\mathcal{L}$ the set of edges $\lambda \in \mathcal{L}$ connecting them. The group of nodes through which pedestrians enter and leave the network are referred to as a set of centroids and are defined as $\mathcal{C} \subset \mathcal{N}$. Two centroids can be connected by a single route $\rho \in \mathcal{R}$, which is defined as a sequence of edges $(\lambda_1, \lambda_2, ...)$.

The concept of route demand can then be defined as the number of users leaving the origin node $v_0$ during time interval $\tau$ with destination $v_d$. Therefore, we define $d_{p,\tau}$ as the number of users following route $\rho$ and starting it at departure time interval $\tau$. We extend this into a time-space expanded vector $d = [d_{p,\tau}]$.

2.2.2 Available information

Our model is based on the fact that some network observations are available: directed flows and/or subroute flows. They can either be actual measurements on the network or inferred from a model (e.g. train-induced flows, Nicholas Molyneaux).

Directed flows

A directed flow $f_{\lambda,\tau}$ represents the number of users entering at link $\lambda$ during time interval $\tau$. We define $a_{(\lambda,\tau),(\rho,\kappa)}(d)$ as the probability that a user associated to the route $\rho$ and departure time interval $\kappa$ reaches link $\lambda$ during time interval $\tau$. Then, the directed flow can be expressed as:

$$f_{\lambda,\tau} = \sum_{\rho \in \mathcal{R}} \sum_{\kappa = 0}^\tau d_{\rho,\kappa} a_{(\lambda,\tau),(\rho,\kappa)}(d)$$

We can rewrite this formula in matrix form by considering $f = [f_{\lambda,\tau}]$ and $d = [d_{\rho,\kappa}]$ as time-space expanded vectors, and the matrix $A = [A_{(\lambda,\tau),(\rho,\kappa)}]$, where $A_{(\lambda,\tau),(\rho,\kappa)} = [a_{(\lambda,\tau),(\rho,\kappa)}]$. We then get:

$$f = A(d)d$$

where $A$ is the assignment matrix that maps route demand to link flows.

Subroute flows

Same as before, we can define the subroute flow $g_{r,\tau}$ as the number of users entering a certain subroute $r < \rho$ during time interval $\tau$. Then, we can also express it as:
Chapter 3. Dynamic demand estimator for uncongested networks

\[ g_{r,\tau} = \sum_{\rho \in \mathcal{R}} \sum_{\kappa = 0}^{\tau} d_{\rho,\kappa} b_{(r,\tau), (\rho,\kappa)}(d) \]

which in matrix form is

\[ g = B(d)d \]

where \( B \) is the assignment matrix that maps route demand to subroute flows.

### 2.2.3 Estimation

The problem of estimating demand can then be expressed as the problem of finding the OD demand vector \( d \) such that the available network measurements match at best with the corresponding mappings.

\[
d = \arg\min_{d \geq 0} (\mu_1 \| A(d)d - f \|_2^2 + \mu_2 \| B(d)d - g \|_2^2 + \mu_3 \| d \|_2^2)
\]

where \( \mu_1 \) and \( \mu_2 \) are weights depending on the measurement we want to use. Since this problem is underdetermined, the solution is chosen subject to a minimum-norm condition. Therefore, a third term \( \mu_3 \| d \|_2^2 \) has been added to guide the solution towards the one with minimum norm. Several solvers have been tested and an active set method solving the KKT conditions for the non-negative least squares problem has been set as being the most efficient one.

### 2.3 Case study: Lausanne railway station

A case study of Lausanne railway station has been made to demonstrate the applicability and possibilities of the demand estimator that has been developed.

#### 2.3.1 Description

Using the walking areas of Lausanne railway station as a test case, pedestrian flows occurring during the morning peak hour are investigated. Especially, the 30-minute period between 07:30 and 08:00 is considered.

Figure 3.1 shows a schematic map of Lausanne railway station. Platforms (yellow centroids) are connected by two pedestrian underpasses referred to as PU West and PU East. The pedestrian walking network is represented by a blue graph connecting centroids and intersection nodes. Pedestrian counters are represented by red dots, while the areas covered by a pedestrian tracking system are coloured in green.
The following data is available:

- **ASE data:** pedestrian counts registered by sensors placed in the main entrance and exit areas of Lausanne railway station (in red in figure 3.1). Directed flows or link flow counts can be obtained from this data.

- **VisioSafe data:** disaggregate trajectory recordings in the green areas of Figure 3.1. Subroute flows in these areas can be obtained after processing the data.

2.3.2 Results

Since we have no information about the real demand, a direct validation can not be made. However, some consistency checks can be implemented to test our model. From the VisioSafe data we can obtain the measured demand, which will be slightly shifted in time because the trajectory recordings start at the pedestrian underpasses, far from the origin of the routes (OD nodes). However, since the aggregation is made by the minute and the distances are relatively short, this shift is not very relevant.
Figure 3.2 shows the overall estimated route demand (i.e. after aggregating the demand of all the routes) for different values of the weights $\mu_1$ and $\mu_2$, depending on whether we want to consider the measurements of the link flows ($\mu_1 = 1, \mu_2 = 0$) or of the subroute flows ($\mu_1 = 0, \mu_2 = 1$). Intermediate weights using both data sources may also be used.

![Figure 2.2: Overall route demand at Lausanne railway station between 07:30 and 08:00 aggregated per minute. The red solid line corresponds to the demand measured from the trajectory recordings. The green and blue dashed lines correspond to the demand estimated using our framework, using as input information ASE data (green) or VisioSafe data (blue).](image)

Since trajectory recordings are available inside the two pedestrian underpasses, from the VisioSafe data we are able to measure the occupation (i.e. total number of pedestrians) at these underpasses for each time interval. Therefore, by defining an assignment matrix $S$ that maps route demand to the occupation of each pedestrian underpass (see Mazars-Simon, 2014, for information about how this matrix is built) we can compute an estimation of the occupation using the estimated route demand as input and compare it with the measured occupation. Figure 3.3 shows the result of implementing this process.
Analyzing the results shown by these plots, it can be clearly seen that our model based on VisioSafe data provides a good estimation of demand, but when the weights of the solver are set so that only ASE data is used, our model can only well estimate the overall demand and the occupation in PU East, but fails in estimating the occupation in PU West.

One possible explanation for this is that the ASE sensors have problems of oversaturation and fail to accurately count pedestrians under heavy congestion. Since PU West has approximately double demand than PU East, this might be the reason why the model fails only on this part. However, the situation is still not well understood and subject to future research.
2.3.3 Visualization

In this section, some graphic visualizations that help to understand pedestrian flows, congestion or even the effects of train arrivals on the studied network are introduced.

Circos plot

This plot represents the accumulated OD demand during a certain time period aggregating the network centroids by groups.

![Accumulated estimated OD demand for Lausanne railway station on January 22, from 7:30 to 8:00. Green, blue and red streams represent flows of pedestrians with origin at station exits/entries, platforms and shops, respectively.](image)

The results appear to be very realistic, in the sense that most of the traffic occurs between North and Metro entries/exits and the different platforms. Also, since the period of study is the morning peak hour, it seems perfectly logic that the flow of pedestrians from platforms to the station exits is bigger than the inverse one, since it is the time where people from towns nearby commute to Lausanne to work.
Dynamic OD map

This plot is optimal to clearly visualize the influence of train arrivals on the route demand. It also allows us to make a consistency check of our estimation model by using the train timetables of the station. If our model is consistent, an expected train arrival in a certain minute would imply, in the subsequent minutes, a clear visualization of route demand having as origin the platform of arrival of that train and as destination the different OD points of the network.

![Dynamic OD map](image)

**Figure 2.5**: OD demand map of Lausanne railway station in January 22, from 7:29 to 7:30. Rows indicate origin points of route demand and columns indicate the destination of this demand. The darker the color of the square, the higher the demand between the pertinent OD points.

From figure 3.5, it is easily appreciated that during the time interval 7:29-7:30, most of the estimated demand has as origin platforms 7/8 and destination to one of the three exit points of Lausanne railway station (north, south and metro exit points). This is clearly the OD demand behaviour generated by the arrival of a train. This gives us an idea of the consistency of our demand estimator, since looking at the train timetable for Lausanne railway station we see that the arrival of a train with origin St-Maurice is scheduled at 7:28 at platform 7.
Dynamic flow map

This plot dynamically shows the flow patterns present in Lausanne railway station as well as the areas under more congestion.

Figure 2.6: Flow map of Lausanne railway station in January 22, from 7:29 to 7:30. The size of the white circles is proportional to the demand at the node that they represent. The color of the edges indicate the number of users passing through in that edge in that time interval.
Chapter 3

Demand-Supply framework

3.1 Introduction

This section presents a framework for dynamically estimating pedestrian demand in congested train stations. To do so, it combines a demand estimator and a demand-elastic pedestrian traffic assignment model.

The motivation behind combining these two models is to obtain a demand-elastic assignment mapping that allows to estimate pedestrian demand in presence of demand-supply interaction. In the long term, the goal is to predict pedestrian demand using train timetables and mobility forecasts.

3.2 Mathematical approach

The travel time $t$ of a user following a certain route and departing at a certain time generally depends on the network condition. Since the later is given by the amount of users using the network, the travel time directly depends on the demand:

$$t = \tau(d)$$

where $\tau$ is a function that computes the travel times given a certain demand vector as input. This is achieved by using a traffic assignment model such as the previously commented PedCTM. The detailed behaviour of this model is not commented here since it is not the goal of this thesis, but information about it can be extensively found in Haenseler et al., 2013.

At the same time, the demand can be estimated based on this travel time distribution:
where $\sigma$ is a function that provides an estimation of the demand vector based on the travel time distribution given by the traffic assignment model.

\[
d = \sigma(t)
\]

Finding the balance between demand and supply implies solving a fixed point:

\[
d = \sigma(\tau(d))
\]

This framework implements a two-step approach such as the one shown in figure 4.2 with the believe to be a reasonable approximation to this fixed point. A Banach iteration is also tested in one of the case studies (see case study(II)). The initial assignment mapping that is used in the a priori demand estimator may be chosen from a free-flow propagation model -assuming a normal distribution of the walking speed ($N(1.34, 0.34)$) or after initializing PedCTM with very low demand.

\[
\text{Demand estimator} \quad \text{PedCTM}
\]

\[
\text{A priori demand estimator} \quad \text{A priori supply model}
\]

\[
\text{A posteriori demand estimator} \quad \text{A posteriori supply model}
\]

**Figure 3.1:** Demand and supply interaction.

**Figure 3.2:** Two-step approach to approximate the fixed point arising from the interaction of the demand estimator and PedCTM.
In order to implement the framework that matches both models, it is necessary to consider the distinct treatment of time and space that the two models apply. Whereas the estimator uses a graph-based space representation, PedCTM follows a more "continuous" cell-based representation (see Haenseler et al., 2013). In a similar way, the discretization of time is done in time intervals in the estimator as it has been previously defined, while in PedCTM this discretization is made in smaller time steps, which are defined in the next section.

3.3 Demand Estimator - PedCTM: Disaggregation

To run PedCTM, two input configuration files are required:

- **Layout configuration file**: describes the infrastructure where the simulation takes place.
- **Demand configuration file**: describes the demand introduced to the flow simulator.

The process to adapt the demand outputed by the demand estimator to the input of PedCTM requires a change in its space and time representation that forces a disaggregation process.

**Time representation**

We will define now the time representation used in PedCTM. With the period of analysis being divided into a set of discrete time steps, each step $\omega$ is of uniform length $\Delta t = t^+ - t^- = \frac{v_f}{L}$, with $v_f$ being the calibrated pedestrian velocity of the flow model and $L$ the cell size.

Due to the different discretization of time implemented in the demand estimator and in PedCTM, we will consider that a time step $\omega \in \tau$ if $t^- \in \tau$, that is, if the time step associated with the supply model starts during the time interval associated with the demand model. With this consideration, a mapping between time intervals and time steps is easily made.

**Space representation**

The two models used in our framework use a different representation of space. The demand estimator uses a graph-based representation of space, while PedCTM follows a more continuous approach by defining the network as a contiguous set of cells. In the process of transforming the demand outputed from the estimator into the proper format for PedCTM, the definition of routes in the two models is our only concern.

In the demand estimator, a route is described by the list of nodes $v \in N$ that define the shortest path in graph $G$ between the two OD nodes. In PedCTM, cells are grouped by zones $z$. A route
\[ \rho \text{ is then described by the list of zones of the cells that define the route. A mapping between nodes and zones is thus necessary and implemented.} \]

**Distribution of demand**

Once the representation of time and space is solved, and since a time interval of the demand model \( \tau \) typically contains several time steps associated with the supply model \( \omega \), a model for distributing the demand among the different time steps \( \omega \) needs to be chosen. Given that we have no further information about how this demand actually behaves inside the time interval, choosing a uniform distribution seems the fairest option.

Uniforming distributing the demand implies an input of demand in each time step, which has a very high computational cost in PedCTM, especially when many routes are present. A demand split factor \( n \) determining between how many equally spaced time steps the demand has to be distributed has been defined to cope with these cases. In a case of time intervals \( \tau \) of 60 seconds and time steps \( \omega \) of 2 seconds (i.e., each time interval containing 30 time steps), \( n = 1 \) would mean placing all the demand in the first time step, \( n = 2 \) distributing it between the first and the middle time step, and \( n = 30 \) uniformly distributing the demand among all the time steps.

A study on how this factor affects the final result of our estimation is conducted in the case study of Lausanne railway station.

### 3.4 PedCTM - Demand estimator: Aggregation

As it has previously been stated, to run the demand estimator an assignment matrix mapping OD demand to link flows is required. This assignment matrix is demand-dependent. PedCTM allows us to set some cells as sensor cells on its simulation, outputing a log book of arrivals for each sensor with information about the departure time step, route, arrival time step and the size of the group of users. Therefore, from PedCTM we can obtain \( M(\rho, \omega_d), (\xi, \omega_a) \), which is the number of users (no need to be an integer number) following route \( \rho \) and starting it at time step \( \omega_d \) that arrive at the sensor cell \( \xi \) during time step \( \omega_a \). Inversely to what has been done in the disaggregation process, this "demand" needs to be aggregated in both time and space:

\[
M(\rho, \kappa), (\lambda, \tau) = \sum_{\omega_d \in \tau} \sum_{\omega_a \in \kappa} M(\rho, \omega_d), (\xi, \omega_a) | \lambda \in \lambda(\xi)
\]

where \( M(\rho, \kappa), (\lambda, \tau) \) represents the number of users following route \( \rho \) and departing at time interval \( \kappa \) that arrive at link \( \lambda \) at time interval \( \tau \). Each sensor cell \( \xi \) is mapped to a link \( \lambda \) and the PedCTM time units or time steps to the corresponding time interval for the demand estimator.
Time is discretized in bigger units in the estimator, so an aggregation over time needs to be made.

Since the links $\lambda$ are mapped from sensor cells, they represent the links for which measurements of flows are available. In order to build the assignment matrix of link flows, a transformation into probabilities needs to be made. This is simply done by dividing the number of users taking route $\rho$, departing at time interval $\kappa$ and arriving at link $\lambda$ at time interval $\tau$ by the total number of users with the same route and departure time but with different arrival times.

$$A(\rho, \kappa, \lambda, \tau) = \frac{\sum_{\omega_d \in \tau} \sum_{\omega_a \in \kappa} M(\rho, \omega_d), (\xi, \omega_a) | \xi \in \xi(\lambda)}{\sum_{\tau' = \kappa} \sum_{\omega_d \in \tau'} \sum_{\omega_a \in \kappa} M(\rho, \omega_d), (\xi, \omega_a) | \xi \in \xi(\lambda)}$$

where $A(\rho, \kappa, \lambda, \tau)$ is the probability that a user associated with route $\rho$ and departure time interval $\kappa$ reaches link $\lambda$ during time interval $\tau$. Since this assignment matrix comes from a demand-elastic supply model (PedCTM), it is dependent on demand.
3.5 Case study (I): Lausanne railway station

3.5.1 Description

The framework connecting the two models has been tested in pedestrian underpass west of Lausanne railway station. This underpass connects all the train platforms of Lausanne station to its main exits. Typically, pedestrians move from one platform to one of the exits, or the other way around. Given the high number of OD nodes, there’s a big number of possible routes. However, Lausanne is not a very congested railway station.

![Diagram of Pu West](image)

**Figure 3.3:** Graph-based space representation of PU West used in the demand estimator (left) and cell-based representation used in PedCTM (right).

3.5.2 Results

As commented, this test case presents a large number of possible routes, making all the computations very expensive. For this reason, only a two-step approach has been followed, i.e. only one iteration -leading to a prior and a posterior estimate of demand- has been made.
Figure 3.4: Error of the posterior and prior estimates of demand when compared to the measured demand for the different values of the demand split factor, i.e. for the different ways of disaggregating the demand.

3.6 Case study(II): Bottleneck

We have applied our framework to another scenario with different characteristics than Lausanne railway station.

3.6.1 Description

This is an experiment carried out at Delft University of Technology (Daamen, W, and Hoogendoorn, SP (2003): Controlled experiments to derive walking behaviour, European Journal of Transport and Infrastructure Research). People were asked to walk through a short corridor that got narrower at the end, simulating a bottleneck. Only two OD points are present and therefore only one route is possible. The demand at the entrance is smoothly increased, kept constant for a while and then smoothly decreased during a total time period of 15 minutes. The trajectory of each pedestrian is available, and the travel times vary from 4 seconds (free flow) to 25 seconds (heavy congestion).

In contrast to Lausanne railway station, this is a test case scenario very easy in terms of routes and OD points but demanding in terms of congestion. Here is shown the cell representation for PedCTM of this bottleneck experiment:
3.6.2 Results

For this experiment, a Banach iteration has been implemented with different number of iterations. Apart from this, the fixed-point has been solved using the Newton-GMRES method.

Figure 3.6 shows the measured and estimated demand when two iterations are performed. The Banach iteration is initialized by inputing a very low demand (simulating no congestion) in PedCTM, thus obtaining a first assignment mapping. The demand-inelastic estimator is then ran to obtain a first estimation of demand (estimated demand 0). This demand is then disaggregated and inputed again in PedCTM, repeating the same process. Two iterations, in order to obtain two posterior demand estimations, have been performed in this case.
The difference between the prior demand and the measured demand is very small, and this is because the increase and decrease of demand in this experiment is very smooth. It can be seen that the two posterior estimates of demand are larger than the prior estimate at the beginning and then smaller.

A method for solving the fixed point that supposedly arises in this problem has also been tested (Newton-GMRES). Figure 3.7 compares the error obtained when comparing the estimated demand and the measured demand for the different iterations and using different methods.

\[ \| A(d) \cdot d - f \|^2 \]

**Figure 3.7:** Representation of the squared error obtained when comparing the measured demand and the estimated demand for the different iterations. Two methods are compared: I) The Banach iteration for a total of 50 iterations, II) The Newton-GMRES method to find the fixed point. It needs almost 40 iterations to find this fixed point given a certain tolerance value.

Until convergence is reached, we can see how the value of the error using the Newton-GMRES method jumps around to very high values in certain iterations. The reason for this is that this method tries different solutions every few iterations, therefore misleading to very big errors. The fixed-point is achieved after almost 40 iterations and it can be clearly seen that the demand estimated using this method leads to a smaller error in comparison to using a simple Banach iteration.

The same plot has been made for the solver error, i.e. for the result obtained in the demand estimator when estimating demand using the equation: \( \| A(d) \cdot d - f \|^2 \). Figure 3.8 shows the results for this plot. Same as before, the method Newton-GMRES jumps around in certain values until convergence, as expected. It can also be seen that when using the Banach iteration
the error decreases during the first iterations, but then rises again until converging at a certain value. This can be explained by two facts: I) There is no fixed point in this experiment. Although rare, it may be a feasible explanation. II) There is a fixed point but it doesn’t match with the measured demand. This is the most probable explanation, since the measured demand accounts for errors in the link flow counts.

![Figure 3.8: Squared error of the solver of the estimation framework for both the Banach iteration and the Newton-GMRES methods.](image-url)

**Figure 3.8:** Squared error of the solver of the estimation framework for both the Banach iteration and the Newton-GMRES methods.
Chapter 4

Conclusions

4.1 Conclusions

A flexible framework for dynamically estimate demand in absence of congestion has been developed. This framework has been tested in Lausanne railway station leading to high performance and the possibility to obtain several visualizations that allow us to understand better the pedestrian patterns in this station.

A two-step OD demand solver for congested networks has been developed. It has also been extended with the possibility of having as many iterations as it is desired, as well as the ability to solve the demand-supply problem by solving a fixed point. This framework has been applied to two different case studies with different characteristics:

- Application to PU West, Gare de Lausanne (OD estimation “difficult”, but no demand-supply interaction)
- Application to the Dutch bottleneck experiment (heavy demand-supply interaction but a trivial OD estimation)

4.2 Next Steps

Following PedFlux, the long-term research project in which this thesis takes place, the next step that should be followed is the application of this framework in a case study involving a congested network with abrupt changes in demand. It is a general opinion that in a more challenging case study the prior estimate of demand will be worse and therefore the posterior estimates will significantly improve the estimation.