

Bus Routing Optimisation: A Case Study for the Toulouse Metropolitan Area

Joan Burgalat^{1,2}^a, Gaël Pallares¹^b, Myriam Foucras³^c and Yohan Dupuis⁴^d

¹CESI LINEACT, Campus de Montpellier, Mauguio, France

²ENSAM, Paris, France

³CESI LINEACT, Campus de Toulouse, Labège, France

⁴CESI LINEACT, La Défense, Paris, France

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Abstract: This paper investigates the efficiency evaluation of a public transport using an analysis of Origin-Destination matrices (mOD). The use of a trip-chaining method on the automatically collected transport data provides a realistic and accurate representation of traffic flows characterized by mOD. The introduction of a critical walking distance and an user flow at bus stop allow us to probe possible network configurations and identify the best one in terms of service offer, ecological impact and operational cost. The configurations comparison allows to identify the levers for the transport management. We deploy this methodology on a french case study for the Toulouse Metropole Occitanie region. The main obtained results shows that for a walking distance close to 1000m, the distance per day on a bus line can be optimised by 3km for a time saving close to 20%, representing an annual gain of more than 1ton of CO₂ for a user loss of around 3%. These results suggest that low-cost optimisation of a transport network is possible while maintaining a high-quality, environmentally-friendly service offering.

1 INTRODUCTION

Public transport is a strategic and much-used mode of transport throughout the world. It is becoming increasingly necessary to promote its use and to make this mode of transport more sustainable in order to limit greenhouse gas emissions as CO₂ and pollution. In the USA, public transport represents average 6 billion trips in 2020 and 32.87 billion total passenger miles travelled of which 50% is for travel to work and 37% for shopping and entertainment. On the energy front, there has been a reduction in CO₂ emissions through the use of metro trains instead of private cars and a shift in the bus fleet towards hybrid buses (7% in 2010 for 18.8% in 2020), leading to a reduction in the use of fossil fuels (Dickens, 2023).


In Asia, domestic passenger transport is expected to increase by 2.6% between now and 2030, ris-


ing from 16 trillion passenger kilometres in 2018 to around 22 trillion in 2030. However, it is predicted that CO₂ emissions will increase by 1.1%. Although there is a slowdown in CO₂ emissions, the forecasts suggest that the objectives of the Paris Agreement on climate change will not be achieved (Sudhir Gota, 2023).


In EU, use of public transport increased by 70% overall between 2000 and 2019, although there was a decrease in some countries (Poland, Slovakia, Greece, etc.).


It should be remembered that in the EU road transport represents average 96% of transport sector greenhouse gas emissions, although there has been a decrease since 2008 which continues to accelerate (ADEME, 2023).

Regular use of public transport has become an important part of the demand for transport networks. Before the COVID-19 crisis in France, regular use of public transport hovered around 70% (UTP, 2022) with a peak in 2019 (73%) with a high proportion of bus mode use (around 40%). Post COVID-19 use is estimated at 53% in 2021, with a recovery to 59% in

^a <https://orcid.org/0009-0006-1726-0804>

^b <https://orcid.org/0009-0002-8680-604X>

^c <https://orcid.org/0009-0002-3673-8528>

^d <https://orcid.org/0000-0002-9725-2049>

2022). However, 41% of French people do not use public transport while the transport sector is the main source of greenhouse gas emissions (MinisterForEcology, 2022).

Public transport is an important part of working life and is constantly growing to meet the ever-increasing demand due to demographic growth and urban densification. To meet this demand, it is becoming important to optimise transport networks. To do this we need to be able to quantify and evaluate network efficiency. Some authors have already worked on this issue. The notion of transport network efficiency is a complex one: we can cite six major issues such as cost, service, congestion, sustainability, social inclusion and accessibility, the relevance of these issues varies depending on the observer viewpoint. Daraio et al. propose a framework with a reading grid weighted to take this particularity into account (Daraio et al., 2016). For example, Hrelja explains that there are a number of important factors involved in assessing the effectiveness of networks. These include quality of service (waiting times, journey times, punctuality and clarity of information). However, these points can also depend on the geographical area (urban or rural) and the travel objectives: for work, we expect frequent departures and a high level of punctuality; ticketing systems must be simple and integrated, and vehicles must be comfortable (Hrelja et al., 2020). Moreover, others factors such as bus frequency, journey time or distance travelled, are directly linked to the network and bus routing and have an impact on the network's response to demand, as well as having an impact on the environment. Network-dependent points can be measured from data collected during bus passages. Distance and travel time are linked to stops imposed by the bus route to meet user demand. A standard way of assessing demand is to estimate the origin-destination matrix.

In the context of sustainable cities, it is important to work on the various levers to reduce the transport network's footprint. Considering the CO_2 emission rate for a bus (around $900 - 1000 \text{ g/veh.km}$) and car (around $150 - 200 \text{ g/veh.km}$) in France (INFRAS, 2023), it takes between 5 and 7 cars to emit as much CO_2 as a bus. Looking at short-distance journeys ($< 100\text{km}$), statistics show that 1.4 people on average (MinisterForEcology, 2019) occupy a car. A bus will be more profitable than a private car, if there is a flow of people at each stop in the interval $[7, 10]$. In this work, we propose an innovative approach to optimise a transport network from an ecological and an economic point of view. The objective is to reduce greenhouse gas emission while maintaining quality of service, simply by analysing ADCS data. Daily OD

matrices are estimated using the trip chaining method described above. The passenger flow per stop (number of people using the stop to get on and off) is then computed. The introduction of a critical walking distance and an user flow at bus stop allow us to probe possible network configurations by removing bus stops and route modification thanks to the Open Source Routing Machine (OSRM) software. By considering various constraints such as the flow at stops and the acceptable walking distance threshold, we can optimise the bus route.

- Decrease journey times and distance travelled
- Reduce greenhouse gas emissions

The paper is structured as follows: first, we introduce the experimental setup with the public transport network and the available data. Next, the methodology is presented with an explanation of Trip Chaining Method and the algorithm we developed. Subsequently we present the results obtained and the discussion section offers an analysis of the results and opportunities for further researches.

2 METHODOLOGY

2.1 Data Collection

The development and management of the network is based on the data collected, whether ticketing data when validating the ticket or location data collected with the Operations Support System. General Transit Field Specification (GTFS) files contain network information (lines, timetables, stations, etc.) The combined use of location and ticketing data provides precise spatio-temporal information on how passengers use the network. Based on the data mentioned, we used the mODs of a high service level bus lines to test our method. Those mODs matrices represent regular season ticket except for unique validation ticket or tickets with multiple validation. Those trips take place outside the school holidays and at weekends. On a thursday in october 2019, around 24000 passengers used this line, knowing that there 80 passages in one way. Those data represent a high level bus line and do not consider travel on demand transport.

2.2 mOD Reconstruction

An Origin-Destination Matrix is a matrix that describes the number of users a_{ij} who boarded at origin i (row) and alighted at destination j (column). This tool is used to represent the demand placed by

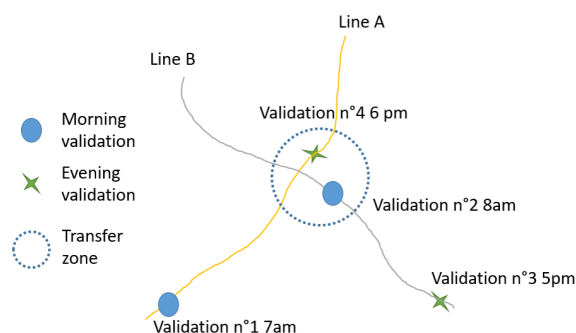


Figure 1: Displacement reconstruction using TCM.

users on the transportation network. Originally conducted through surveys, mODs are now established using Automatic Data Collection Systems (ADCS) data, which is more cost-effective and easier to implement. Networks can be divided into two categories: closed networks, where users validate both at entry and exit, and they have a fare dependent on the distance travelled; and open networks, where users only validate at boarding, and the fare is independent of the distance travelled. For closed networks, establishing an mOD is straightforward. However, for open networks, it is necessary to estimate the user's alighting stop. Various methods exist for this, including the Trip Chaining Method (TCM) (Alsger et al., 2016; Hora et al., 2017), which utilizes ticketing and geographical data, as well as the different boarding locations throughout the day to chain the journey and determine alighting stops. For example, the use of ADCS data to estimate mOD (Cui, 2006; Wang et al., 2011; Huang et al., 2020), the identification of factors influencing modal change (Ji et al., 2019; Li, 2016) or the evaluation of the effectiveness of combining different methods and/or datasets (Feng et al., 2018; Osorio and Punzo, 2019; Ge and Fukuda, 2016; El Mahrsi et al., 2014). The above examples suggest that mODs can be used to optimise public transport networks.

In our case study, the mODs were reconstructed using the trip chaining method (TCM). This method is based on transport data (ticketing, Operating Support System, etc.) and is used to reconstruct a passenger's journey on the network based on multiple validations on the same day. TCM is based on various principles that aim to describe the logic of user choices during multiple-validation journeys. These include:

1. The alighting stop is the same stop as the next boarding stop or the nearest stop to the next boarding stop.
2. The last stop of the day is the same as the first boarding stop or the stop closest to the first boarding stop.

3. To make a connection, users agree to walk a certain distance less than a threshold distance.

This is an approximate method and those simplification due to principles implies some errors. Hussain in (Hussain et al., 2021) explain that TCM has average 90% of success. For more information on the principles governing TCM, please consult (Hora et al., 2017).

In figure 1, a passenger travels on the network and his various validations are collected at different times. The validations correspond to the different journeys made by the passenger on the network. One of the principles of TCM is that the passenger gets off at the stop closest to his new stop. We can therefore deduce the locations of the alighting and the time using the GTFS and reconstruct the mOD.

2.3 Network Optimisation Method

Towns are becoming denser and populated leading to an increasing of pollution and need for mobility. In view of the current crisis in public health, the need to improve air quality and climate change linked to greenhouse gas emissions, we need to consider all possible solutions to limit the impact of the players involved in this situation. One possible solution is to remove bus stops that are not used very often and then calculate the shortest bus route and then reduce greenhouse gas emission.

In our case study, we have chosen a line in the Tisséo Collectivités network and the objective is to determine which stops on this line are few used and to see what effects the removal of these stops would have on the network response (number of passengers not picked up, number of km covered, etc).

To carry out this analysis, we chose to consider two constraints: the first is the flow at the stop, i.e. the number of people using the stop (boarding and alighting). The second is the acceptable walking distance. We retrieve the flow value N_i at the stop i being evaluated and compare it with a flow threshold value N_T . If the flow at the stop is smaller than the threshold flow, we remove the bus stop and the flow of the removed stop N_i is put to zero. The distance threshold will determine if users of the removed bus stop are lost in the worst case or reported to the nearest stop. Indeed, we calculate $D_{i-1,i}$ which is the distance between stop i and stops $i-1$ and $D_{i,i+1}$ which is the distance between stop i and $i+1$. If at least one of the distances is smaller than the threshold distance D_T , then users from bus stop i are transferred to the nearest stop implying an user walking between both bus stops. The walking distance users to reach the nearest stop is calculated using the OSRM application in

walking mode. Otherwise, the users are considered to have been removed for the public transport users. For a given distance threshold and a given flow threshold, the bus line is evaluated and if some bus stops are removed, the distance travelled and the travel time by the bus are computed with the OSRM application in driving mode. The algorithm used to achieve this is shown in Algorithm 1.

```

Data: List_inter_stop_distance,
         List_stop_flows
Initialization;
for  $N_i$  in List_stop_flows do
    if  $N_i < N_T$  then
        The stop is removed
        for  $D_i$  in List_inter_stop_distances
            do
                if  $D_{i-1,i} < D_T$  or  $D_{i,i+1} < D_T$ 
                    then
                        Users go to the nearest stop;
                         $N_{\min(D_{i-1,i}, D_{i,i+1})} + = N_i$ ;
                         $Walking\_distance + =$ 
                             $N_i \times \min(D_{i-1,i}, D_{i,i+1})$ ;
                    else
                        Users are lost;
                         $Loss + = N_i$ ;
                    end
                end
            end
             $N_i = 0$ ;
        else
            end
            Calculation of the new bus route (distance
            and duration);
        end
    end

```

Algorithm 1: Optimisation and bus routing calculation algorithm.

3 RESULTS

3.1 Experiments

We propose a case study on the public transportation network in Toulouse, managed by the entity Tisséo Collectivités, which plans, organizes, and evaluates its mobility policies. The network is made up of 2 metro lines with 27 km of track, 2 tram lines with 24.8 km of track, an urban cable car (Téléo, the longest in France) with 3 km of track, 10 High Service Level Buses and around a hundred bus routes covering 1494 km. The intention to develop a sustainable and responsible service includes specific facilities in the study area, such as park-and-ride facilities and bike

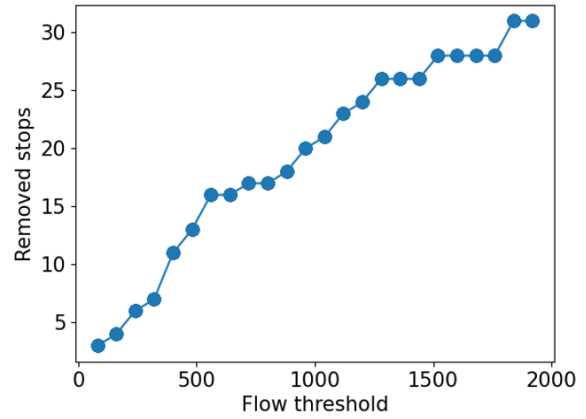


Figure 2: Removed stops as a function of flow threshold.

park. Additionally, there is a Transport-on-Demand service for an area with over a million inhabitants (Tisséo, 2023).

3.2 Results

In this paper, we present results for one of the High Service Level Bus. On the studied day, around 24000 passengers used this line, knowing that there 80 passages in one way. The line is composed of 38 bus stops and the nominal travelled distance is 14,568 km. Figure 2 shows the number of stops removed from the line as a function of the flow threshold values chosen. The graph shows an increasing trend, as the higher the flow threshold, the more likely it is that a stop will be cancelled. In order to achieve the objective of reducing CO_2 , the minimum flow value accepted is 7 people per stop. With 80 symmetrical passages per day, this amounts to a minimum threshold of 560 people using the stop per day. A graphical reading, confirmed by data analysis, shows that for a daily flow of 560 people per acceptable stop, half of the stops on the line will be cancelled.

Figure 3 represents the ratio of people lost on the line as a function of the threshold flow value and the acceptable walking distance in the form of a heat matrix. It can be seen that quality of service will be affected for acceptable walking distances of less than 350m, whatever the flow. For distances greater than 350m, we can see that the ratio of people lost is very low, which is explained by a stop reassignment because the median inter-stop distance is 346m. Therefore, there is a one-in-two chance of finding a consecutive stop within 350 metres, hence the completely blue zone above 400 metres, as very few people are lost.

When bus stops are removed, users have to walk to the nearest bus stop. The figure 4 represent the walking distance that users have to cover. This dis-

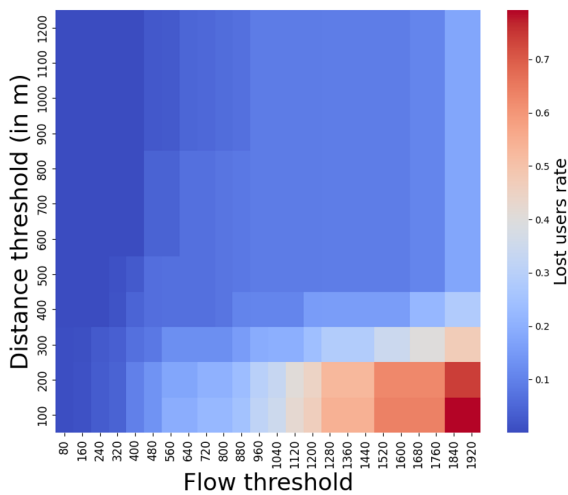


Figure 3: Rate of people lost per flow threshold and distance threshold.

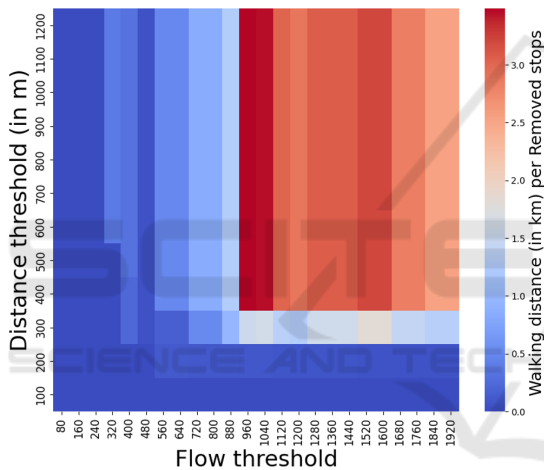


Figure 4: Walking distance per removed stops as a function of distance and flow threshold.

tance is a function of the flow threshold and the distance threshold i.e. the distance that users are willing to walk, however those distances do not represent an one-way displacement and not a round trip.

For example, whatever the flow threshold value, for acceptable walking distances below 250m, users will have to walk an extra-distance of 500m on the network to reach a stop. From 250m to 350m, the distance to be covered is of the order of a kilometre. Beyond 350m, there is a fracture at a flow threshold of 880 users per stop. For flows above this cut-off, users will have to walk more than 2km, but for lower flows the maximum walking distance will be close to 1km.

Figure 5 shows the bus distance travelled reduction (difference of the distance travelled by the bus between ante and post optimisation) as a function of flow threshold. It can be seen that the curve has an in-

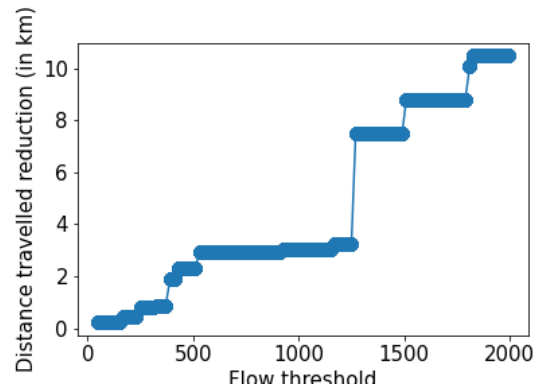


Figure 5: Travelled distance reduction as a function of the flow threshold.

creasing trend, but with levelling off phenomena, particularly from a flow threshold equal to 560 users per stop. In this case, the bus reduces its travel distance by 3km per trip. For flow thresholds between 560 and 1300, the gain in distance is very small because the removal of stops does not change the bus route in this range, the removed stops are aligned and the rerouting of buses is therefore not significant. Beyond this range, the gain in distance is around 8km, as the removal of several consecutive stops is likely to lead to a change in the route and therefore the use of another route.

4 DISCUSSION

The question is how the optimisation by stop deletion affects the service quality. We have therefore plotted on the figure 6 the distribution of users lost due to a stop being cancelled (influence of flow threshold, cf. Figure 2) and as a function of the acceptable walking distance.

The number of people lost is inversely proportional to the acceptable walking distance. For example, for a flow threshold of 560 people per trip and an acceptable walking distance threshold of 100m, we lose 4651 users, whereas for a walking distance threshold of 1200m, we lose around 601 people. For a total attendance of 24000 people in the worst-case scenario, this amounts to a loss of 20% of people, whereas in the best case losses are estimated at around 3%.

The choice of a daily flow threshold of 560 per stop informs us that the losses will be contained in the interval [3%, 20%]. From figure 5 we can see that the value of 560 corresponds to the start of the first stage in achieving a significant saving in distance travelled of 3km per day and a time saving of around 20%. This time gain can be an opportunity to increase the buses

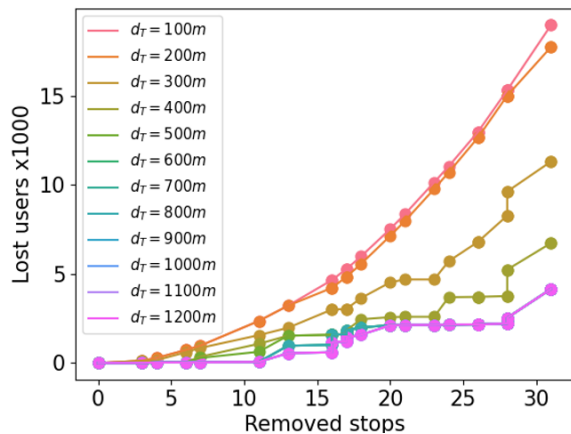


Figure 6: Number of lost users as function of the number of removed stops for different walking distance threshold (d_r).

services frequency. Furthermore, the additional walking distance that users will have to cover to reach a replacement stop is between 500m and 1km.

Given that the average bus consumes between 50 and 60 litres of fuel per 100km, we can calculate a saving of between 240L and 288L per day and for this line. On the other hand, the CO_2 emission rate is in the range of [900, 1000] g/km, thus for a reduction of 3km per trip on a line corresponds to a reduction of CO_2 emissions in the [432, 480] range kg per day for a given bus line. If we extend the result to the bus network of more of than 100 bus lines, this represents several dozens of tons of CO_2 per day and then several dozens of thousands of tons of CO_2 per year. However when bus stops are removed, users should take another transportation mode for example bike sharing, transport for demand, taxis or private car. On the one hand, environmental parameters may favour the use of certain transportation mode for example the weather, congestion network, distance to cover or proximity with city centre, etc. On the other hand, socio-economical parameters age, household composition, employment, etc. The use of carbon modes generates emissions that need to be taken into account. Some studies prove that people are more likely to walk in their neighbourhood if there is a bus station is located at less than 400m (Boulangue et al., 2017). Moreover, public transport user are more likely to walk, between 400m and 800m, to reach their stop (Reck et al., 2022).

The analysis of the figure 4 provides relevant informations but lacks realism, as it seems that the walking distance is the main factor. However, in our study the walking distance threshold does not depend on few parameters that can influence the evaluation of the acceptability threshold. For example, the weather, the topography of the site (slope, layout of pedes-

trian zones) or natural barriers such as a river. Hussain in (Hussain et al., 2021) has already raised this point. Moreover, our assessment of the ecological impact takes into account the number of people at the stops, but the comparison in terms of CO_2 emissions between car and bus takes into account a journey, i.e. an inter-stop journey. A possible improvement to our study would be not to take into account only the flow of people at the stops, but also to include the occupancy of the bus. If occupancy is below the threshold, we consider that the network is not optimised in terms of CO_2 emissions. The model that we propose is sufficiently simple to be implemented but there is some phenomena that we do not consider. Firstly removing stops will increase the demand on the other bus stops so the boarding duration will increase and so on the pollution due to the longer dwell time. Secondly there is some factors that can raise greenhouse gas emissions that our model don't take into account for example the traffic congestion, vehicle types, travel speed or acceleration deceleration rates. Moreover the CO_2 emission is calculate with (INFRAS, 2023) which take into account vehicle type, years and type of engine. It will be interesting to take into account some other factors to estimate more precisely the CO_2 emission, for example the speed, driving style, distance or vehicle load. Thirdly, we need to know the passenger's behaviour, if a stop is removed, some passenger will not go to the nearest stop but may be they will use different transportation mode such as private cars, taxis, transport-for-demand that can increase the greenhouse gas emission.

5 CONCLUSIONS

With the world's population constantly on the increase, there is a growing demand for mobility. With public transport systems under increasing strain, it is important to find ways of meeting demand efficiently. At the same time, the ecological impact of transport must also be taken into account. To this end, we propose a method for optimising a bus route in terms of distance travelled, while measuring the impact on quality of service and greenhouse gas emissions. Our results show that for a flow threshold value of 560 users per stop, the number of stops removed corresponds to half of the stops on the line. It was found that the rate of people who would no longer have access to the public transport service would be between 3% and 20% depending on the accepted walking distance of 1200m and 100m respectively. With regard to greenhouse gas emissions, the reduction in emissions is estimated more than 450 kg per day for a given bus

line which represents a reduction of more than 150 tons per line and per year. Compare to references in the literature (Stewart and El-Geneidy, 2016) explain that bus stop consolidation is effective and simple to the quality of service, and conclude that remove average 23% bus stops and reducing the system coverage area by 1%. In addition (Kehoe, 2004) show that bus stop consolidation improve timetable reliability and has no negative impact on ridership, and can even improve it.

This study is an initial effort to examine the feasibility of solutions to reduce the carbon impact on the environment, while also assessing the impact on quality of service. Our model is not perfect and needs to be modified to include more factors in the quantification of greenhouse gas emissions. However, we also need to assess the influences and trends on the choice of mode of transport when there is a modal shift.

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