*Proceedings of 7th Transport Research Arena TRA 2018, April 16-19, 2018, Vienna, Austria*

# Implementation of User Driven Innovation methodology to estimate Origin-Destination Matrices and to deploy tailored bus routes

Samir Awad-Núñez[a], Miguel Álvarez Martínez[b], Adrián Fernández Carrasco[c], Rafael Barriuso Maicas[d], Nicolás Escudero Prieto[e], Marta Serrano Balbuena[f], Paula Botella Andreu[g]

[a]: *PhD in Civil Engineering, Associate Professor at Department of Civil Engineering, Universidad Europea Madrid. Escuela de Arquitectura, Ingeniería y Diseño, Calle Tajo, s/n, 28670 Villaviciosa de Odón, Madrid, Spain.*

[b]: *MSc in Civil Engineering, CEO at Hécate Ingeniería S.L., Calle Churruca 15 Bajo exterior derecha, 28004 Madrid, Spain.*

[c]: *BSc in Civil Engineering; Partner at Hécate Ingeniería S.L., Calle Churruca 15 Bajo exterior derecha, 28004 Madrid, Spain.*

[d]: *MSc in Telecommunications Engineering, CTO at Tribalyte Technologies S.L., Glorieta de Quevedo 8 6º2, 28015 Madrid, Spain.*

[e]: *PhD in Physics, CEO at Tribalyte Technologies S.L., Glorieta de Quevedo 8 6º2, 28015 Madrid, Spain.*

[f]: *MSc in Civil Engineering, Chief of Communications & Consultancy office at EMT (Empresa Municipal de Transportes de Madrid), Calle Cerro de la Plata, 4, 28007 Madrid, Spain.*

[g]: *BSc in Civil Engineering, Project Engineer at Hécate Ingeniería S.L., Calle Churruca 15 Bajo exterior derecha, 28004 Madrid, Spain.*

**Abstract**

As a new solution to estimate OD-M of transport and to design tailored bus routes, the project B_us (commercial name of the project FitYourBus, funded by the European Commision H2020 programme frontierCities) proposes a new way of collecting and treating mobility pattern data in order to reduce about 36% the cost of data acquisition and 41% the cost of exploiting data, allowing the deployment of user-driven transport services. The proposed methodology includes the following stages: 1) Platform. Deployment of a back-end service and its administration interfaces. The data collection set-up is based on a client-server architecture using J2EE and Docker technologies; 2) Data collection. Users provide their basic commuting data –origin, destination, work hours, etc– using our cross-platform smartphone app, which communicates with the back-end service; 3) Data treatment. The collected data stored in a database is converted into a proper OD-M through an algorithm that combines Dijkstra's and A*algorithms, running as a MapReduce job on a Big Data Apache Hadoop engine. Single citizen objective optimization algorithm influences the development of the multi-objective optimization branches in the problem (maximizing the overall time savings for the participants at the same time as maximizes the number of passengers per bus).

To test the methodology and validate the correct implementation of the algorithm, a pilot project has taken place in coordination with EMT, the main bus public company in the city of Madrid (Spain). The trial consisted in deploying employees' bus routes to reach to and to go from one of their operation centres (involving about 1,300 workers, including drivers, mechanical technicians, and other workers). Mobility patterns data of 30.8% of them were obtained. After running the algorithm, the result was a set of vectors (one from each user), which was exported to a GIS platform to plot the first "draft corridors" surrounding the routes that go through the most repeated nodes. These corridors were particularized for the conditions of circulation of the buses and according to the schedules of the daytime and night-time of the rest of employees' routes of EMT and the current public transport services in the metropolitan area. Results show that operation times of the two current employees' routes have been reduced between 1.2% (but improving spatial coverage and frequencies) and 44.1% while has been increased the fleet utilization ratio because the service passes to be used by workers who previously did not use it (with a majority change from the car to the bus).

*Keywords: Origin Destination Matrix; Smartphone app; Transportation demand; Transportation planning; Multi-objective optimization.*

## 1. Introduction

B_us is an innovative system to generate or adapt buses routes tailored to the user´s needs: Trough our app, users are surveyed to obtain their commuting needs (origin, destination, number and times of travel, etc). These data is then processed through our algorithm in order to obtain cost-effective buses routes that can be implemented in the ground by the client. This new methodology implies having the essential data for a fraction of the cost and overcomes most of the major problems of current Demand Responsive Transport (DRT) systems.

Furthermore, engagement and reputation improvement can be reached: Thus, by using the B_us app and analysis it is possible to generate a virtuous cycle, where the transport authorities and operators develop a positive image on fulfilling their responsibilities towards the population and at the same time empowers the users as source of information.

The main objective of this paper is to bring to light a new solution to the School Bus Routing Problem (SBRP) applied to the deployment of special regular bus services. The proposed methodology implies the use of a smartphone app and Mixed Algorithm, combining Dijkstra's with A*, parallelized thanks to Hadoop technology.

This paper starts with a brief historical review of the development of DRT systems. This summary enables to identify the main problems of the old systems which our proposal overcomes. Then, the B_us methodology is described in detail. To test the capability of this methodology, a case study is presented. It shows that the services derived from the obtained results are better than those of the current transport services. Finally, these results are discussed and the main conclusions of this research are presented.

## 2. Bus Routing Problem: a brief overview

B_us aims to reduce the cost of mobility data collection and analysis with the development of a smartphone/web app able to gather information from users and, with this, minimize their trip disutility and maximize the efficiency of the vehicles deployment. It is because the inputs provided through this app are later processed to create an OD-M used to calculate the bus route that best fits the needs for the whole of users, but maximizing the bus occupation. This approach to public transportation could be conceived as integrated into the DRT.

### *2.1. The School Bus Routing Problem and the first round of DRT systems*

DRT is not any new, it comes from the SBRP that is commonly considered first formulated in 1969 by Newton and Thomas (Park and King, 2009). Starting in the 70s, different authors saw the potential of this problem when applied to public transportation, especially in those areas where traditional systems were unable to provide a complete service (Ellis and McCollom, 2009): rural areas, sprawl areas, isolated areas of a city; services in evenings or weekends; or by integrating new users (such as accessibility to disables or co-worker commuters).

There was then a first round of implementations that, due to the lack of technology, used call centres as the necessary link between users and transportation modes. Nevertheless, these projects failed because a number of reasons mostly related with the lack of coordination and cooperation between DRT and traditional transport systems and bad marketing, poor identification of demand, financial issues and technology limitations (Teal, 1994). Since large scale, complex network DRT systems required high tech equipment to operate efficiently, three sustainable market niches where commercial operators can target for DRT services were specified (Enoch et al., 2006):

1. Low tech, small scale simple systems in areas where users are willing to use any form of public transport but are only able to pay low fares. E.g. school bus in rural areas shared with other residents who need it to commute to work since there is not another form of public transportation available.

2. Small scale simple to operate systems for users who appreciate luxury and are prepared to pay a premium for a service that is as far away from a bus or a minicab as possible. E.g. airport shuttles.

3. Modifying the current systems providing savings of time or increasing the number of user by offering a service that allows tackling an area, need or user that has not been previously considered, to be cost effective.

Traditional DRT services have often been criticised because of their relatively high cost of operation, their lack of flexibility in route planning and their inability to manage high demand.

*2.2. Innovations and advanced techniques in systems: the second round of DRT systems*

The potential for overcoming these limitations was realised through the introduction of new technologies (Mageean and Nelson, 2003). Thus, due to the evolution in programming able to solve the SBRP and on board geo-positioning systems, the costly technology barrier might had been overpassed, making feasible more complex and ambitious systems, able to move away from call centres, allowing DRT cease to be a small scale system and back to its initial conception as a scheme able to provide service to areas and groups of people that had been left out by tradition modes of transportation.

The programing methods of the first years of the 21st century enabled to formulate a multi-objective approach that has been used to study different transportation related issue: trade-offs between operator fuel consumption cost and passengers travel time in railways (Ghoseiri et al., 2004); headway optimization (Chianjiao et al., 2008); trade-offs between users and operator interests in public transport systems (Mauttone and Urquhart, 2009); minimization of passengers and operator cost (Fan et al., 2009); effect of real-time optimization of public transport systems in the users waiting time (Cortés et al., 2010); public door-to-door service transportation systems (e.g.: dial-a-ride with time-window) optimization (Chevrier et al., 2010); bi-modal (private vehicle and bus) urban road network optimization, (Miandoabchi et al., 2011); etc.

In order to solve the multi-objective approach metaheuristic algorithms are being widely used. The most popular are Genetic Algorithms as, unlikely traditional methods (Cevallos and Zhao, 2006). However, as the Genetic Algorithms are computationally intensive optimization techniques, its application to large and complex problems is limited and further optimizations are needed (Agrawal and Mathew, 2004). Some of these improvements include: 1) Ant Colony Optimization which helps to find the best path through graphs. This method has been used, for example, by Kuan et al. (2006) to solve the feeder bus network design able to connect regular bus stops with the rail network; or by Euchi and Mraihi (2011) to solve the SBRP in urban areas applied to the Tunisian case. 2) Tabu Searh that allows doing local neighbourhood searches of a potential solution. Two references applying this algorithm are, for example: Fan and Machemehlm (2008), when authors optimize the public transport network with variable demand; and Bruni et al. (2014), to design robust routes for DRT systems. 3) Parallelization (division of the problem into smaller ones that can be computed simultaneously), that has been uses by Yu et al., 2011, in bus route headway optimization.

As a consequence, as stated Davison et al. (2014), in the UK, since the early 2000s the number of DRT systems is been increasing steadily. It is mainly because the technological improvement and spread of internet equipped smartphones, which allow more quickly deployments. But it is also due to the social trend of rapidly ageing population and higher levels of unemployment, which makes the development for non-private transport increasingly important in order to avoid social exclusion; and to cuts in public transport subsidy budget. This trend seems to be comparable to what might be happening in the rest of Europe and North America, where a second attempt to apply DRT systems has been developed. Examples of these new systems can be seen in Helsinki, Washington DC and New York.

In this second round of DRT systems, technology does not seem to be the restrictive factor; this time around, the coordination and goals alignment (or lack of them) between involved agents and a cultural barrier that makes many users to approach the system with skepticism show that, in order for these systems to succeed, a change of mind-set is needed. This is evident in Davison et al. (2012) who argue that a deep cultural shift is required to improve the public perception of DRT as a viable transport option. In this sense, DRT systems must cover the passenger needs (Jokinen et al., 2011). However, he also found some barriers that might lead current implementation example to failure, highlighting the trade-off between the need of a critical mass to make the system viable and the low usability when the system becomes too complex for some users. This problem is also described by Ronald et al (2013): many-to-one current services usually suffer from underutilization, but also that demand consisting of shorter trips leads to lower running times and vehicle kilometre per vehicle, which, from the user's point of view means that increased demand led to higher excess travel for each individual, in addition the waiting time is affected by the amount of demand, the size of the service area, and the average desired trip length.

### *2.3. B_us as a starting point for a third round of DRT systems*

A further improvement that might contribute towards the successful implementation of DRT systems is the introduction of the discretionary concept into the equation. The need of a critical mass to guarantee sustainability, defended by Jokinen et al. and Ronald et al., goes against the usability of the system since, as more users demand the system, the individual utility is reduced. As said in Ronald et al (2013), if the total mass is divided into homogeneous groups with common needs, the demand can be increased maintaining the utility for individual users, helping to transform the attitude of people towards this system, motivating them to use it instead of the private car. Also, this contributes to reduce the issue of rivalry with traditional form of public transportation, since the system is conceived as a complement to public transport in areas that the habitual system is unable to cover: connection between the last public stop and the workplace. Other improvement of the B_us system is to place the user at the core of the innovation process, engaging them into the design of the routes they are going to use. According to De Moor et al (2010), a way to reach success in innovative projects is to able users to integrate their knowledge into them. In this case, we encourage them through a communication campaign (easier with homogeneous groups with common needs) inviting them to participate by providing us with their commuting data (they must provide their origin, destination and shift, in the B_us app). The more data we obtain the more usable and accurate the routes can be. At the moment it has not been possible to evaluate the deployment of the routes but the idea is go beyond merely asking users for feedback after the piloting phase and correct the routes with these opinions.

## 3. Methodology

The B_us methodology can be summarized as follows:

*STAGE 1: Base platform setup*

This stage involved the configuration and deployment of a back-end service, including its administration interfaces. The main function of this service is providing the APIs over the Internet so data sent by client applications can be collected by the server. The back-end technologies used for the implementation of this service were: J2EE, Spring Boot, MongoDB and Docker. The service runs on a Docker container which is deployed on a VPS on the cloud.

*STAGE 2: Data collection*

In this stage, the client mobile applications were made available to users through the standard distribution mechanisms (i.e. publishing the apps on Google Play, Apple AppStore, etc). The apps store that provided data on the back-end service mentioned above via JSON messaging over HTTPS. The mobile applications used cross-platform technologies such as Ionic Framework, AngularJS, PhoneGap/Cordova. They also integrate push notifications via APNs and GCM/Firebase.

*STAGE 3: Algorithm development*

B_us uses a Mixed Algorithm, combining Dijkstra's with A*, designed as a MapReduce job to be run on an Apache Hadoop big data cluster. With it, single citizen objective optimization algorithm influences the development of the multi-objective optimization branches in the problem.

Dijkstra's is an algorithm able to find the shortest path from one node to all others in a network. It has been employed, for example, to process and give a response to the queries that a traffic information system receives from a railroad networks (Schulz et al. 1999) and to obtain the shortest distance from every pick-up point in the SBRP (Li and Fu, 2002). We used it to reduce the disutility of individual users by minimizing access distance and travel time (calculating it as the Euclidian distance between each pair of nodes divided by the mean operating speed of a bus). It involves minimizing the metric (Equation 1):

$$ {}_{n}\vec{U}^{t}_{route\ i,j} = \sum_{1}^{n}\left(\alpha \cdot {}_{n}t_{i,i'}, \beta \cdot {}_{n}t_{i',i'}, \gamma \cdot {}_{n}t_{i',j}\right) \quad \text{(Eq 1)} $$

where:

${}_{n}\vec{U}^{t}_{route\ i,j}$ represents the disutility of each route for all the users taking only travel time into account,
n is de number of users,
${}_{n}t_{\ i,i'}$is the walking time to access from the origin to the first bus stop and from the last bus stop to the destination,
${}_{n}t_{\ i',i'}$ is the in-vehicle time from the first to the last bus stop,
${}_{n}t_{\ i',j}$is the waiting time since user arrives to the bus stop until bus comes,
${}_{n}t_{\ i,i'}$, ${}_{n}t_{\ i',j}$ and ${}_{n}t_{\ i',i'}$ are weighted by α, β and γ to take into account time perceptions:

$$\alpha = \begin{Bmatrix} 1.2;\ {}_{n}t_{\ i,i'} \le 10 \\ 1.3; 10 < {}_{n}t_{\ i,i'} \le 15 \\ 1.4; 15 < {}_{n}t_{\ i,i'} \le 20 \\ \infty; 20 < {}_{n}t_{\ i,i'} \end{Bmatrix} \qquad \beta = \begin{Bmatrix} 1.1;\ {}_{n}t_{\ i',i'} \le 5 \\ 1.2; 5 < {}_{n}t_{\ i',i'} \le 10 \\ 1.3; 10 < {}_{n}t_{\ i',i'} \le 15 \\ \infty; 15 < {}_{n}t_{\ i',i'} \end{Bmatrix} \qquad \gamma = \begin{Bmatrix} 1;\ {}_{n}t_{\ i',j} \le 20 \\ 1.1; 20 < {}_{n}t_{\ i',j} \le 40 \\ 1.2; 40 < {}_{n}t_{\ i',j} \le 60 \\ \infty; 60 < {}_{n}t_{\ i',j} \end{Bmatrix}$$

When search has too many possibilities, and benefiting from the advantages of parallelization, the following condition is established to make the solution converge at a higher speed without implying a poorer quality of the solution (since there are two later phases, one to maximize occupation and one of human expert analysis):

$$-\eta \cdot \left(\frac{\partial \varepsilon}{\partial x_{ij}}\right)^{t} + \zeta \cdot \left[(\partial x_{ij}\ )^{n} - (\partial x_{ij}\ )^{n-1}\right] \le \mu \cdot \left\| {}_{n-1}\vec{U}^{t}_{route\ i,j} \right\| \quad \text{(Eq 2)}$$

being

$$\varepsilon(p) = \frac{1}{2} \cdot \sum_{i=1}^{k} \left( \left\| {}_{n}\vec{U}^{t}_{route\ i,j} \right\| - \left\| {}_{n-1}\vec{U}^{t}_{route\ i,j} \right\| \right)^{2} ;\ \frac{\partial \varepsilon}{\partial x_{ij}} = \sum_{i=1}^{k} \frac{\partial \varepsilon(p)}{\partial x_{ij}} \quad (x_{ij} \text{ are } {}_{n}t_{\ i,j},\ {}_{n}d_{\ i,j},\ {}_{n}ivo_{\ i,j})$$

and when η, ζ are the coefficients that vary to convert Equation 4 in a square system of equations (that means it is determinate and compatible) and to make true the inequality giving μ the value of 0.01.

On the other hand, A* is a *best-first search* algorithm, meaning that it solves problems by searching among all possible paths to the solution for the one that incurs the smallest operational costs. This algorithm does not come from the field of transportation –its main and most recent contributions are on the area of path planning for robot's mobility, as can be seen in Yao et al. (2010) and Duchoň et al. (2014)–, but is very useful to refine the draft paths defined with the Dijkstra's algorithm. As can be deduced from the text above, when working with discretionary transport, increasing in-vehicle occupation does not have a dramatic effect on increasing the marginal disutility of each user. From the discrete number of the best options obtained through the Dijkstra's results, A* runs correcting them to include not only the paths with the shortest travel time but also those with less distance travelled and most in-vehicle occupation (establishing a maximum of 90 passengers/bus), and finding the optimal path among all options reducing the number of buses needed, which implies the optimal operational costs. The optimization condition is to satisfy Equation 3 for each pair of nodes:

$$R_c \text{ fulfilling } [\min( {}_{n}t_{\ i,j}) \wedge \max( {}_{n}ivo_{\ i,j})] \wedge [\min( {}_{n}d_{\ i,j}) \wedge \max( {}_{n}ivo_{\ i,j})] \quad \text{(Eq 3)}$$

where:

$R_c$ represents the solutions to be assessed taking into account travel time, distance travelled and in-vehicle occupation,
${}_{n}t_{\ i,j}$ is the travel time for each user,
${}_{n}d_{\ i,j}$ is the distance travelled by each user,
${}_{n}ivo_{\ i,j}$ is the in-vehicle occupation.

*STAGE 4: Data processing*

The collected user data stored in the back-end database is converted into a proper OD-M in several steps. Firstly the data was converted into the proper format that can be consumed by the route optimization algorithm. In this process context information was added, such as the current bus stop geo-position, codes (for later identification) and the trip time between bus stops. This input data preparation was made though custom NodeJS scripts running on the data processing back-end. Then, the algorithm ran. During the process, the routing algorithm aimed at maximizing the overall time savings for the users, using as inputs a node graph (composed by the users origin and destinations plus the bus stop nodes), several adjustable factors such as waiting time and walking time to the closest bus stop and fulfilling the condition of Equation 3. The algorithm took the data stored in CSV files in Hadoop Distributed File System (HDFS) and produced the route calculations also in CSV files in Cosmos' HDFS. The output data generated by the algorithm (in textual format) was exported to geographical analysis software to display them on a map, allowing human-readable routes that represented the envelope curves of the routes that takes the set of users. Once all routes are represented, a heat map simulating the envelope curves of the routes that takes the set of users was performed. With the heat map curves and representing in a grayscale the number of times each node is crossed, it is possible to draw the preliminary possible routes. To these routes are applied three operational corrections: 1) the envelope curve is forced to go through the most repeated nodes and those in which a greater number of users start its trip; 2) the route is corrected according to the directions of movement of the streets; 3) the route is corrected according to the traffic conditions and to the itineraries of night buses in Madrid. This point requires the agreement with the responsible for the operation in the company.

## 4. Case of study: how to deploy commuter bus routes for the Madrid's bus company employees

Usually software testing is considered as one phase of the software developments life cycle. In this sense, B_us, as innovative software based project, is not an exception. In addition to the small tests performed to verify each step, the complete methodology was tested with a real case.

### *4.1. Framework*

To test the methodology and validate the correct implementation of the algorithm, a pilot project has taken place in coordination with Empresa Municipal de Transportes de Madrid (EMT), the main bus public company in the city of Madrid (Spain). Transport of workers takes into account an homogeneous group of users and the company's internal communications allows to reach a significant number of workers and this to involve them in the design of the new routes (as the workers are who benefit from the improvements of these routes, it means more obtained data). EMT has four Operation Centres in Madrid, but among them, the test was focused only on the Entrevías Operation Centre (EOC). The main reason to select this centre is related to its location: next to the railway lines in the periphery of the city, in an area without urban continuity that causes a lack of a solid offer of public transport. It is a problem for the more than 1,300 workers who start or finish their workday in the EOC, especially for bus drivers who have to start and finish the regular buses services early in the morning and later in the night and can't afford their commuting by public transport.

EMT operates an only for workers bus line devoted to provide an access to their works to the EOC. Nevertheless, the schedule and route of this line hasn't changed in the last decades, and the Unions wanted to adapt these routes to the current demand. Using the B_us app, we surveyed the personnel of the EOC. More than 30,8% of the workers that commute to or from EOC participated in the test, providing the essential data of their daily commuting needs. We treated this data as have been shown in Section 3 in order to provide EMT with alternative routes to improve their current services to this centre.

### *4.2. Results and discussion*

After running the algorithm, the result was a set of vectors (one from each user), which was exported to a GIS platform to plot the first "draft corridors" surrounding the routes that go through the most repeated nodes. These corridors were particularized for the conditions of circulation of the buses and according to the schedules of the daytime and night-time of the rest of employees' routes of EMT (those that the new routes are not going to replace) and the regular public transport services in the metropolitan area. The obtained routes can be compared to the current employees' routes. Comparison between the current services and the pilot project results is shown in Table 1 and Figure 1. The current and future commercial speed (measured as average speed, including buffer times and trip time) is considered the same for each route and shift. The results of bus service production (in vehicle·Km) and capacity (in passengers per hour) are compared for each line. Regarding user by user, the proposal operation times of the new employees' routes reduce between 1.2% (but improving spatial coverage and frequencies) and 44.1% and the new routes increase the fleet utilization ratio

Table 1. Comparison between the current services and the pilot project results.

| | | Route name | Origin | Destination | Route length (km) | Buffer (min) | Trip time (min) | Loop time (min) | Average speed (Km/h) | Number of vehicles | Schedule* | Number of services | Interval (min) | Veh·Km | Pax/h |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| West route | | | | | | | | | | | | | | | |
| Current | Origin morning | P-19 v2-3 | Villaverde | EOC | 30.0 | → | → | 60 | 29.95 | 1 | 4:00 to 6:00 | 2 | 60 | 59.91 | 80 |
| B_us | | R1 | Príncipe Pío | | 34.7 | 3 | 77 | 80 | 27.00 | 2 | 1:30 to 7:30 | 3 | 40 | 104.10 (+74%) | 120 (+50%) |
| Current | Origin afternoon | P-20 v4-29 | Legazpi | EOC | 10.7 | → | → | 40 | 16.08 | 1 | 6:30 to 13:50 | 12 | 40 | 128.68 | 120 |
| B_us | | R1 | San Cristóbal | | 23.4 | 5 | 85 | 90 | 16.50 | 3 | 7:30 to 13:30 | 12 | 30 | 280.80 (+118%) | 160 (+33%) |
| Current | Destination morning | P-20 v4-29 | EOC | Legazpi | 10.7 | → | → | 35 | 18.38 | 1 | 14:15 to 20:00 | 9 | 35 | 96.51 | 137 |
| B_us | | R1 | | Plaza Elíptica | 21.6 | 3 | 72 | 75 | 18.00 | 3 | 13:30 to 19:30 | 12 | 25 | 259.20 (+169%) | 192 (+44%) |
| Current | Destination night | P-20 v30-31 | EOC | Atocha | 15.7 | → | → | 30 | 31.47 | 1 | 23:30 a 1:30 | 2 | 60 | 31.47 | 80 |
| B_us | | R1 | | Plaza Elíptica | 24.0 | 7 | 53 | 60 | 27.00 | 2 | 19:30 to 1:30 | 4 | 30 | 96.00 (+205%) | 160 (+100%) |
| East route | | | | | | | | | | | | | | | |
| Current | Origin morning | P-21 v1-3 | Vallecas | EOC | 19.0 | → | → | 45 | 25.34 | 1 | 3:35 a 6:00 | 3 | 45 | 57.02 | 107 |
| B_us | | R2 | Las Suertes | | 22.8 | 5 | 55 | 60 | 25.00 | 2 | 1:30 to 7:30 | 5 | 30 | 114.00 (+100%) | 160 (+50%) |
| Current | Origin afternoon | There is no service for this route and schedule | | | | | | | | | | | | | |
| B_us | | R2 | San Cristóbal | EOC | 23.4 | 5 | 85 | 90 | 16.50 | 3 | 7:30 to 13:30 | 4 | 30 | 93.60 | 160 |
| Current | Destination morning | There is no service for this route and schedule | | | | | | | | | | | | | |
| B_us | | R2 | EOC | Plaza Elíptica | 21.6 | 3 | 72 | 75 | 18.00 | 3 | 13:30 to 19:30 | 3 | 25 | 64.80 | 192 |
| Current | Destination night | P-21 v13-14 | EOC | Vallecas | 16.8 | → | → | 50 | 20.19 | 1 | 00:00 a 1:40 | 2 | 50 | 33.65 | 96 |
| B_us | | R2 | | Valdecarros | 23.9 | 3 | 57 | 60 | 25.00 | 2 | 19:30 to 1:30 | 3 | 30 | 71.70 (+113%) | 160 (+67%) |

→ Unavailable data

* Comparison between EMT and B_us routes is done only during coincident time slots

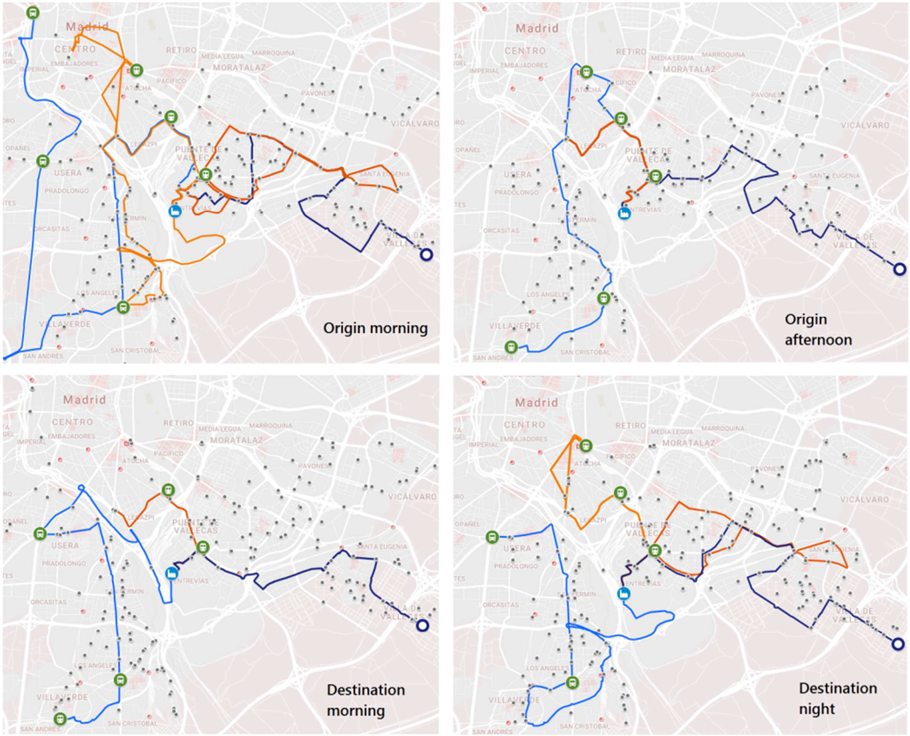


Fig. 1. Bus routes schemes comparing current services with the B_us proposal. Red and orange routes are the current ones. Blue and purples routes are the proposal. Small grey circles are origin or destinations of the users. Big green circles represent the public transport hubs and the big blue circle represents EOC.

As shown in Table 1, the schedule of the current services only serves the beginning and the end of the drivers shifts. However, there are shifts of other staff working at EOC (cleaning, mechanics, administrative...) that require a bus service all day long. For this reason, the pilot project routes include a substantial improvement in the frequency and schedule of service.

Current services are divided into two lines to cover respectively west and east districts of the city. The B_us routes proposal maintains east and west lines, but itineraries are adapted according to the needs of the users (mainly their origin, destination and shift). As can be seen in Figure 1, the current lines run through the city centre. Despite this zone dispose of a huge offer of public transport, has lost their residential function. Furthermore, the last urban development along the south and east areas (where live many EOC workers) lack of public transport services. It means that EOC workers must go to the city centre to use the current line. It increases the length of the workers commuting to EOC and reduces its utility. The proposal overcomes this problem; increasing the space coverage in those spaces were the users live and improving the following issues:

- West route at “destination morning”: current P-19 line runs by the centre without workers. A higher demand can be reached connecting to the public transport hubs of Príncipe Pío, Plaza Elíptica and Méndez Álvaro. The new route incorporates these points along fast roads, reducing the interval from 60 to 40 minutes.

- West route at “Destination morning” and “origin afternoon”: replacing P-20 shuttle, the new service covers the destinations of the south, improving the interval.

- West route at “Destination night”: the new route covers more area with higher demand and runs through some public transport hubs, doubling the current frequency from 60 to 30 minutes.

- East route at all shifts: the current P-21 line covers the districts of Vallecas. This line does not reach the Ensanche de Vallecas, a new urban development along south-east of the city. Proposed lines cover all this new area where live an important amount of the EOC workers.

- East route at “destination morning” and “origin afternoon”: the proposal includes new services for these shifts that have not been deployed before.

- East route at “origin morning” and “destination night”: the interval of the east route is also improved from 50-45 to 30 minutes.

For the set of lines considered (2 routes, 4 shifts per route) the following changes and improvements are observed: 1) Territorial coverage of the lines proposed by B_us is closer to the locations answered in the surveys, whether residences or stations of public transport. 2) In order to achieve intervals of 25-40 minutes that fit most of shifts, it is necessary to increase the allocation of 1 to 2-3 cars per line, increasing the capacity accordingly. 3) The lines proposed by B_us avoid areas with frequent traffic jams (historic centre) reflecting a demographic change where the working population has moved to suburban areas. 4) In addition to the compared lines, there are a few long haul services with 1 or 2 expeditions per day. These services, due to their length (>65 km per loop), are not very effective in terms of cost per passenger. The connection of the B_us lines with hubs of nocturnal public transport is an alternative that covers more zones and schedules than those services.

## 5. Conclusions and limitations

B_us is an innovative project aimed at overcoming the main problems faced by current DRT systems. It implies provinding a demand responsive collective transport service in which the growth of the number of users does not suppose a worse service for each single user. How to achieve this objective? It is easy: selecting services for a homogeneous group of users with common needs (as in the presented case of study, with only one origin/destination) and trying to involve them in the service they want to use.

Through the use of an EMT oriented version of the B_us methodology, we achieved a reduction of 36%* of the data acquisition costs and 41%* of the exploiting data costs (compared to a design with exclusively human analysis) while increasing the engagement of users who feel they are part of the project and are more likely to use the new service. Due to the starting conditions for the pilot project, it was demanded to increase the frequency and the capacity of transport services with the new routes. Results show an increase of yearly production of 166% (measured as vehicles·Km) including routes and shifts unattended before. But this rise is justified by a capacity increase of a 110% in terms of passengers per hour, and a reduction by half in the interval of the most routes. Furthermore, a better matching with the staff schedules has been reached.

However, the methodology needs some improvements since human analysis are still necessary to determine if a bus is circulating in the direction of street traffic, to analyse the turning radiuses and other parameters that are necessary to verify to evaluate the operational viability of the routes, etc. This means that cost reductions may be even higher in the future when automatization of these routines will be carried out. Another limitation, related to the previous one, is the impossibility of providing a service in real time, since it is necessary for users to provide their data in sufficient time to treat them before the service is deployed. However, the Spanish regulatory framework requires the previous authorization of the circulation of the service, so it is a condition that would be inherent to the service even if the analysis were speeded up. The only exception in which this authorization is not necessary is when a discretionary service forms part of a regular itinerary (e.g.: last-mile transport before or after a long journey). In this sense, the limitation can be overcome by collecting the user's origin-destination data while is buying the ticket of the main trip.

Finally, future cases in which the B_us methodology will be applicable are last-mile of long-distance travels (in the case of Spain, through Renfe railway operator and the main intercity bus operators), companies commuting, discretionary transportation of public events (the sale of the service can be a complement to the concert tickets, sports games, etc.) or for private events (such as weddings).

## 6. Acknowledgements

This research was funded by the European Commission H2020 programme frontierCities. We would like to thank the evaluators, who put their trust in us and our coaches for tracing the project in all the different phases. We are also grateful to Madrid City Hall, to the Madrid’s Transport Authority (Consorcio Regional de Transportes de Madrid), and to the Madrid’s bus company (Empresa Municipal de Transporte) for supporting this research when it was only an idea, being essential to obtain the funding and allowing the test deployment.

---

* This results are compared with a set of 100 different bidding prizes for route deployment studies in Spain from 2000 to 2016. It is also expected that these results will be improved as the *experience curve* of this new methodology is traversed and when the tasks that have not been automated become automated.

## 7. References

Agrawal, J., Mathew, T. V., 2004. Transit route network design using parallel genetic algorithm. Journal of Computing in Civil Engineering, 18(3), 248-256.

Bruni, M. E., Guerriero, F., Beraldi, P., 2014. Designing robust routes for demand-responsive transport systems. Transportation research part E: logistics and transportation review, 70, 1-16.

Cevallos, F., Zhao, F., 2006. Minimizing transfer times in public transit network with genetic algorithm. Transportation Research Record: Journal of the Transportation Research Board, (1971), 74-79.

Chevrier, R., Liefooghe, A., Jourdan, L., Dhaenens, C., 2010. On optimizing a demand responsive transport with an evolutionary multi-objective approach. Annual Conference on Intelligent Transportation Systems, Madera Island, Portugal, pp. 575-580.

Chianjiao, S., Wei, Z., and Yuanqing, W., 2008. Scheduling combination and headway optimization of bus rapid transit. Journal of transportation systems engineering and information technology, 8(5), 61-67.

Cortés, C. E., Sáez, D., Milla, F., Núñez, A., and Riquelme, M., 2009. Hybrid predictive control for real-time optimization of public transport systems' operations based on evolutionary multi-objective optimization. Transportation Research Part C, 18, 757-769.

Davison, L., Enoch, M., Ryley, T., Quddus, M., & Wang, C., 2012. Identifying potential market niches for Demand Responsive Transport. Research in Transportation Business & Management, 3, 50-61.

Davison, L., Enoch, M., Ryley, T., Quddus, M., Wang, C., 2014. A survey of demand responsive transport in Great Britain. Transport Policy, 31, 47-54.

De Moor, K., Berte, K., De Marez, L., Joseph, W., Deryckere, T., & Martens, L. (2010). User-driven innovation? Challenges of user involvement in future technology analysis. Science and Public Policy, 37(1), 51-61.

Duchoň, F., Babinec, A., Kajan, M., Beňo, P., Florek, M., Fico, T., & Jurišica, L. (2014). Path planning with modified a star algorithm for a mobile robot. Procedia Engineering, 96, 59-69.

Ellis, E. H., McCollom, B. E., 2009. Guidebook for rural demand-response transportation: measuring, assessing, and improving performance (Vol. 136). Transportation Research Board.

Enoch, M., S. Potter, G. Parkhurst, M. Smith, 2006. "Why do Demand Responsive Transport Systems Fail?" In Transportation Research Board 85th Annual Meeting, 22–26 January 2006, Washington DC: The Transportation Research Board.

Euchi, J., Mraihi, R., 2012. The urban bus routing problem in the Tunisian case by the hybrid artificial ant colony algorithm. Swarm and evolutionary computation, 2, 15-24.

Fan, L., Mumford, C. L., and Evans, D., 2009. A simple multi-objective optimization algorithm for the urban transit routing problem, IEEE Congress on Evolutionary Computation (2009) 1–7.

Fan, W., Machemehl, R. B., 2008. Tabu search strategies for the public transportation network optimizations with variable transit demand. Computer-Aided Civil and Infrastructure Engineering, 23(7), 502-520.

Ghoseiri, K., Szidarovszky, F., Asharpour, M. J., 2004. A multi-objective train scheduling model and solution. Transportation Research Part B, 38, 927-952.

Jokinen J. P., Sihvola T., Hyytiä E., Sulonen R., 2011. Why urban mass demand responsive transport? IEEE Forum on Integrated and Sustainable Transportation Systems (FISTS), Vienna, Austria.

Kuan, S. N., Ong, H. L., Ng, K. M., 2006. Solving the feeder bus network design problem by genetic algorithms and ant colony optimization. Advances in Engineering Software 37 (2006) 351-359.

Li, L., Fu, Z., 2002. The school bus routing problem: a case study. Journal of the Operational Research Society 53, 552–558.

Mageean, J., Nelson, J. D., 2003. The evaluation of demand responsive transport services in Europe. Journal of Transport Geography, 11(4), 255-270.

Mauttone, A., Urquhhart, M. E., 2010. A multi-objective metaheuristic approach for the Transit Network Design Problem. Public Transport (2009) 1:253-273.

Miandoabchi, E., Farahani, R. Z., Dullaert, W., Szeto, W. Y., 2012. Hybrid evolutionary metaheuristics for concurrent multi-objective design of urban road and public transit networks. Networks and Spatial Economics, 12(3), 441-480.

Newton, R. M., Thomas, W. H., 1969. Design of school bus routes by computer. Socio-Economic Planning Sciences, 3(1):75-85. In: Park, J. and Kim, B. I. 2010. The school bus routing problem: A review. European Journal of Operational Research, 202(2): 311-319.

Ronald, N., Thompson, R., Haasz, J., Winter, S., 2013. Determining the viability of a demand-responsive transport system under varying demand scenarios. In Proceedings of the Sixth ACM SIGSPATIAL International Workshop on Computational Transportation Science (p. 7). ACM.

Schulz, F., Wagner, D., & Weihe, K. (1999, July). Dijkstra's algorithm on-line: An empirical case study from public railroad transport. In International Workshop on Algorithm Engineering (pp. 110-123). Springer, Berlin, Heidelberg.

Teal, R. F., 1994. Using smart technologies to revitalize demand responsive transit. Journal of Intelligent Transportation System, 1(3), 275-293.

Yao, J., Lin, C., Xie, X., Wang, A. J., & Hung, C. C. (2010). Path planning for virtual human motion using improved A* star algorithm. Information Technology: New Generations (ITNG), Seventh International Conference, pp. 1154-1158.

Yu, B., Yang, Z., Sun, X., Yao, B., Zeng, Q., Jeppesen, E., 2011. Parallel genetic algorithm in bus route headway optimization. Applied Soft Computing, 11(8), 5081-5091.