A DYNAMIC PUBLIC TRANSPORT ASSIGNMENT MODEL WITH STATIC STRATEGIES FOR INCIDENT MANAGEMENT

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ABSTRACT

This paper proposes a dynamic transit passenger assignment model as part of a simulation model for public transport networks. The simulation model is based on i) a mixed supply model with capacity constraints, queue models, and fail-to-board estimations, ii) a static user choice model based on a generic strategy generation model and assuming that passengers use the predefined travel strategies under normal situations, and iii) a dynamic transit assignment model for network loading. This model has been tested using real data from the C-5 Line (Madrid regional railways) provided by RENFE Cercanías. Two tests have been used for simulating different transport system configurations and states and evaluating the simulation accuracy. The statistical plots obtained with our testing tool show the system response under some configurations of our model.

Keywords: *Dynamic transit assignment, transit network, schedule-based, capacity constraints, simulation*

1.- INTRODUCTION

Technological developments in computer systems have enabled a large number of advances in the real time control of public transport systems. These advances have lead to the construction of intelligent transportation systems (ITS) that give real-time assistance to transport operators. In the research area of ITS and operative planning, the construction of automated support decision systems involves various areas of transport systems like traffic management, traveller information, vehicle operation and control, etc.

Apart from automating the control of normal situations, it is also necessary to provide tools that aid transport operators when they deal with abnormal situations such as emergencies or disturbances on a transport system. Although operators usually address the problem by using their previous experience and their common sense, there are several transport planning software packages (QRSII, URBAN/SYS, VISUM, or EMME/2) which provide a good enough approach to evaluate the effects of operative problems and the decisions taken in response to incidents.

The dynamic transit assignment models for predicting the response of the demand are also a very powerful tool when dealing with incident management, especially when they are considered as part of a simulation model. An extensive review of transit assignment models for simulation purposes can be found in Nuzzolo (2003a, b) and in the articles cited by Lam and Bell (2003) and Wilson and Nuzzolo (2004). Fung et al. (2005) indicate the importance of the few practical approaches (Nielsen (1998), Friedrich and Wekeck (2004), or Crisalli and Rosati (2004)) against the many theoretical advances in the field of transit assignment models. Crisalli (1999) also indicates that this kind of approach allows the evaluation of some network characteristics like timetables, fare structures, etc.

In this paper, we present a dynamic transit assignment model used as part of a simulation model designed to help public transport operators in taking the best decisions in cases of incidents considering not only their previous experience, but also the predicted response of the system. This proposal should be seen as an evolution from the one employed in the generic incident management system developed by Garcia et al. (2009) where the emergency effects are reduced by reassigning fleet vehicles using a simulation-based method.

Simulation models, like the one proposed in this paper, usually comprise a supply model, a path choice (or user choice) model, and an assignment model (Nuzzolo (2003a)). Although there is a lot of literature on assignment models, there are few papers with a practical approach similar to ours. The contributions made by Tong and Wong (1998, 1999 and 2001), Poon et al. (2004), Hamdouch and Lawphongpanich (2008), and Schmöker et al. (2008) are closely related to the aims of our approach.

Considering the previous components of simulation models and the emergency context of this paper, our approach is as follows:

- Given the practical approach considered for our model, we have decided to use a mixed supply model similar to the one presented in Tong and Wong (1999). The capacity constraints are introduced explicitly as fixed vehicle specifications, the queue models in the stations are created with no priority, and a fail-to-board probability is measured when boarding passengers. These features allow simulation profiles of the evolution of the queue size in stations, the number of passengers travelling on the vehicles, or the fail-to-board probabilities.

- As we deal with emergencies, we have decided to use a static user choice model based on the hypothesis that users do not change their behaviour because they are unaware of the existence of the incident. Because of this, a generic strategy generation model can be used such as those proposed by Nguyen and Pallottino (1988), Spiess and Florian (1989), De Cea and Fernandez (1989), or Comminetti and Correa (2001). The problem when applying these strategy generation models is to consider frequency-based networks instead of a schedule-based network like ours.

- The emergency context (which is considered in our proposal in order to simplify the user choice) and the practical approach allow us to focus on the network loading approach. Our proposed dynamic transit assignment model is schedule-based and can be classified, following the proposed classification by Nuzzolo (2003b), as part of a Network Loading Problem.

The remainder of this paper is organized as follows: in Section 2 we describe the supply network, Section 3 describes some demand characteristics and the strategy generation model which represents the static user choice model; in Section 4 the dynamic transit assignment model is shown focusing on the network loading approach as part of the simulation model employed to evaluate the system capacity and response, Section 5 lists all test data taken with a railway network computational test using real data from Madrid's regional rail services, finally Section 6 discusses potential applications of our model and indicates some future improvements.

2.- THE SUPPLY NETWORK

According to Nuzzolo (2003a), the most common types of supply models are: the diachronic network based on three subgraphs which describes the service network as a discrete graph with space-time nodes and space-time arcs proposed by Nuzzolo and Russo (1993) and applied in Nuzzolo et al. (2001) or Nguyen et al. (2001); the dual network by Añez et al. (1996) later used by Moller-Pedersen (1999) which is an important way of network representation when many turning movements or interchanges must be considered; and the mixed supply model initially used by Tong and Richardson (1984) and which has been widely used in the literature (e.g. Tong and Wong (1998, 1999 and 2001) or Poon et al. (2004)).

As a dynamic approach is employed in our proposal, the simulation model is based on a mixed supply model similar to the one proposed in Tong and Wong (1999). This approach is schedule-based so it removes ambiguity and represents the vehicle movements more accurately than the classical frequency-based approach (Poon et al. (2004)), which is more convenient when dealing with practical approaches. Our mixed supply network comprises the following elements:

- <u>*A physical network*</u>: representing the public transport infrastructure via a graph $G^f = (N, A)$ where N is the set of nodes and A is the set of edges. This network also defines a V set which is the fleet of vehicles, where each vehicle $v \in V$ has an associated capacity k_v defining the passenger volume which can travel on it.

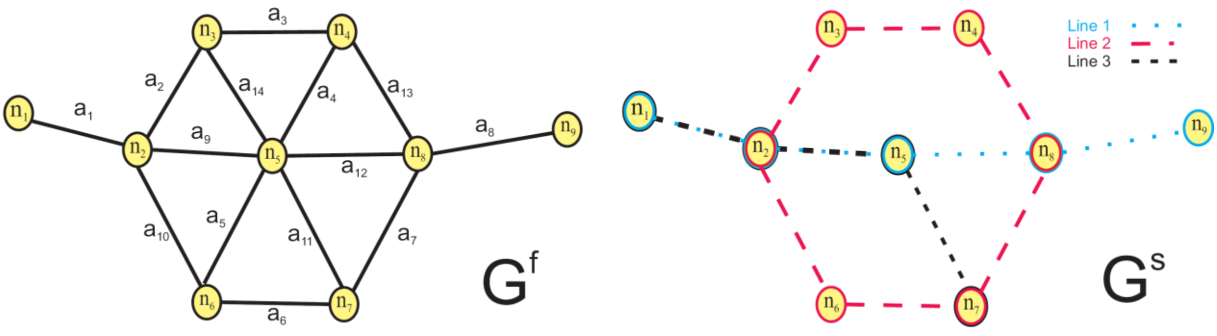

Figure 1: Physical (left) and service (right) graph example

- <u>*A services network*</u>*:* this is the supply system defined by a graph which is set over the previous G^f physical graph. This graph is defined as $G^s = (L, S)$ where L is a set of transit lines and S is a set of services (or runs). For each line $\ell \in L$, a subset of services $S^\ell \subseteq S$ is defined where each service $s \in S$ comprises a vehicle $v \in V^\ell \subseteq V$, an associated service capacity k_s (closely related to vehicle capacity k_v), and a service direction $w = \{+, -\}$. A line service timetable θ^ℓ describes each vehicle run in a more accurate way by using a structure like Table 1. Each service s has a departure instant t_n^s from a station node n defined by the line service timetable. These instants are called *events* because they are those moments in which the system can change, so they must be taken into account when the system is simulated.

Table 1: Line service timetable example

Service	Direction	Vehicle	Capacity	Line services timetable θ^ℓ				
				n_1	n_2	n_5	n_8	n_9
s_1	+	v_1	k_{s_1}	7:15	7:30	8:30	8:45	9:00
s_2	+	v_2	k_{s_2}	10:00	10:15	11:15	11:30	11:45
s_3	-	v_1	k_{s_3}	10:45	10:30	9:30	9:15	9:00
s_4	-	v_3	k_{s_4}	13:50	13:35	12:35	12:20	12:05
...	...	...	...	...	...	...	...	...

- <u>*A demand network*</u>*:* which introduces along with the previous elements a new set $G^d = (C, \Gamma)$ where C is the set of centroids where demand is generated and a set of links defining demand access/exit links Γ. These links connect each centroid with a unique node (which is considered as a station) $n \in N$ in the physical network. The travel time of access links is considered to be homogeneous, so the travel time t_c has the same value for each centroid $c \in C$. In those cases where a centroid could be associated with several stations, we consider that dummy centroids can be considered for each station without any added cost (see Figure 2).

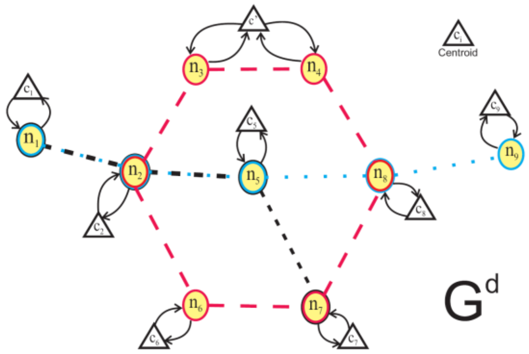

Figure 2: Graphical representation of demand network G^d

3.- DEMAND CHARACTERISTICS AND USER CHOICE MODEL

In this section, we are going to set out some characteristics of the demand which will be taken into account when the dynamic transit assignment model will be described. Finally, we explain the user choice that has been modelled in our simulation model with a static approach by using a generic strategy generation model.

3.1.- Demand representation: packages

Public transport users need to be represented in some way because an efficient evaluation of how demand is influenced by different system states must be provided. For this purpose, passengers are represented using an entity called *package* which is an object that allows an accurate representation of the demand movement.

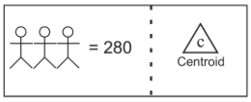

Figure 3: A package example

A package p comprises two different elements: the first element $r_p \in \mathbb{R}^+$ defines the package demand volume as a positive real number which is the total number of passengers represented by the package; the second element $c_p \in C$ defines the destination of all passengers contained in the package. Considering these elements and a set of packages $\mathcal{P}$ we define that two packages $p, q \in \mathcal{P}$ are *homogeneous* if they have the same destination centroid, i.e. $c_p = c_q$. For homogeneous packages it is of interest to define the following operations:

- $p + q$ is considered as the *fusion* between two homogeneous packages. The result of a fusion operation is a new homogeneous package p' with $c_{p'} = c_p = c_q$ and $r_{p'} = r_p + r_q$.

- $Excision(p, \pi)$ is considered as the *excision* of a package into two homogeneous packages by using a proportional constant $\pi \in [0,1]$. The results of this operation are two homogeneous packages p and p' where $r_{p'} = (1 - \pi) \cdot r_p$ and $r_p = \pi \cdot r_p$.

The first operation occurs when two homogeneous packages are travelling in the same vehicle or are waiting in the same queue. The second arises due to the vehicle capacity constraint. When a whole package cannot be totally loaded into a vehicle, this operation allows the boarding of the part of the package which actually fits into the vehicle by using the π parameter as a fail-to-board probability measured at boarding time.

3.2.- Demand generation and distribution

Having defined the main characteristics of the supply network and the representation of passengers in the public transport system, it is necessary to define how demand is generated. Taking a closer look at our system, it can be seen that demand claims to be defined according to two different, but closely related, measures:

- *Flow measures:* are evaluated in terms of objects/time (e.g. passengers/hour). So these types of units have a continuous and time-dependent character and must be used for the dynamic considerations of our problem.

- *Volume measures:* are essential to enable vehicle capacity constraints and package volume representations. The units used are number of objects, such as number of passengers.

Demand flows are modelled in terms of a dynamic demand function $\delta_{c_i,c_j}(t)$ which indicates the flow of passengers between two centroids at instant t. Demand volumes can be calculated by integrating demand flows with respect to time. Considering the time interval (t_1, t_2) and N_{c_i,c_j} as the volume of passengers/users that wish to travel from centroid c_i to centroid c_j, N_{c_i,c_j} can be calculated as:

$$N_{c_i,c_j} = \int_{t_1}^{t_2} \delta_{c_i,c_j}(\xi) d\xi \qquad (3.1)$$

The calculation of equation (3.1) can be made using any integration formula, for example by application of the trapezoidal compound or any other similar method. The $\delta_{c_i,c_j}(t)$ function represents a demand intensity function which may be defined arbitrarily. This demand distribution function is defined by two elements: an origin-destination demand matrix d and a time distribution function $\mathrm{P}(t)$.

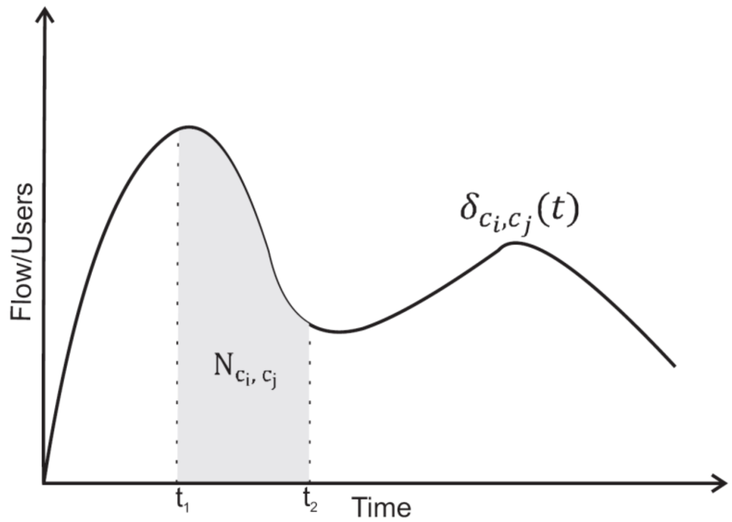

Figure 4: Graphical representation of the relationship between the different measures

O-D matrices are a very common way to represent the prediction of how many passengers want to travel from one origin centroid c_i to a destination centroid c_j. Hence, this element is essential to define the trip/demand generation step as one of the key stages for a demand assignment model. Generally the definition of O-D matrices leads to an estimation of them by using several factors (Ortúzar and Willumsen (2001)) to predict how the demand is generated. Each cell of our O-D matrix d_{c_i,c_j} represents the total passenger volume which will travel from centroid c_i to centroid c_j during a single day.

Together with the O-D demand matrix, some time-dependent considerations must be introduced in order to estimate dynamically the demand volume generated. For this purpose, the second element used in our demand distribution function is a time distribution function $\mathrm{P}(t)$. Although the time distribution function could be defined separately for each O-D pair as $P_{c_i,c_j}(t)$, we consider the same for each link as a simplification because of the limited data about this function provided by RENFE. This function is defined as a piecewise function considering one hour intervals from 5:00 to 24:00 which cover the full daily schedule. Each interval has a value associated which represents the percentage of total daily demand (defined on O-D matrix) which travels during that time period.

At this point, the two elements of our demand distribution are defined making our demand distribution function to be calculated as:

$$\delta_{c_i,c_j}(t) = d_{c_i,c_j} \cdot \mathrm{P}(t) \qquad (3.2)$$

This expression allows an immediate calculation of the formula (3.1) by replacing the definition of demand distribution function. When a package p is generated in the origin centroid c_i and has a defined destination centroid c_p we can define the package demand volume using equation (3.1). To perform this procedure a time interval (t_1, t_2) must be defined depending on attractive services arrival.

3.3.- User choice model: a generic strategy generation model

This part of our simulation model allows the definition of the passenger behaviour. Our model must provide an accurate definition of the route and the services which are considered as attractive for the public transport users. In this section, we introduce the concept of dynamic strategies based on a set of static strategies in order to justify their use and how these strategies are used to simulate passenger movements and decisions.

In the previous subsection, we have defined how demand is represented, generated and distributed. Because we want to evaluate the effects of different system status over the demand, the concept of demand behaviour must be introduced. The demand behaviour has been classically defined by employing the *strategy* concept. Considering a package p which wants to travel from centroid c_p to centroid c_j at instant t we define $E_{c_p}^{c_j}(t)$ as the attractive services, i.e. those services (vehicles or transit lines) which are considered optimal for reaching the public transport user destination at instant t. The calculation of attractive services depends on service frequencies, capacity constraints and waiting queues but it must also consider route choice impact.

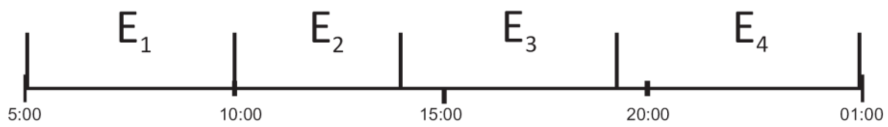

Figure 5: Graphical representation of strategies generation time periods

The $E_{c_i}^{c_j}(t)$ strategies can be defined using a within-day approach and considering different time intervals as in Figure 5. Then we propose that strategies can be calculated using a static user choice model because of the following assumption:

Assumption 1. *Faced with an emergency, it is considered that users do not react because they are unaware of the existence of such an incident and they act in a manner known in advance.*

As we are dealing with and emergency situation, we can use Assumption 1 so users will not change their behaviour during a considered period. Because of this, for a specific instant t the strategies can be calculated using a path choice algorithm which estimates the best path to reach a destination considered by public transport users. This path can be calculated by using several costs like transport mode, fares, travel times, congestion effects or simply by introducing some passenger preferences depending on their previous experience. For our route choice calculation, any static approach like the well known ones shown in Nguyen and Pallottino (1988), Spiess and Florian (1989), De Cea and Fernandez (1989), Comminetti and Correa (2001) or Nguyen et al. (2001) can be used.

A basic hyperpath choice model (Nguyen and Pallotino (1988), Spiess and Florian (1989)) without congestion or capacity has been used for generic strategy generation. With this model, a line-based network representation is used where boarding/alighting nodes have been replicated for each transit line at stations and the line frequencies have been approximated from timetables. For practical purposes, we change the type of strategy generated -considered as a set of attractive nodes for reaching a destination- to a subset of attractive lines and directions to use for reaching a destination.

Considering a package p with an origin centroid c_i and defined by a destination centroid c_p, if this package is generated at instant t we consider that $E_{c_i}^{c_p} = E_{c_i}^{c_p}(t)$ so $E_{c_i}^{c_p}$ defines a set of pairs (ℓ, w). Each of these pairs defines all services from a line ℓ in a direction w as attractive for passengers represented by the package p. Hence, we can define the static strategies by using an O-D strategies matrix E where each cell E_{c_i,c_j} represents the static strategy $E_{c_i}^{c_j}$ which has been calculated for a time period.

4.- DYNAMIC TRANSIT ASSIGNMENT MODEL

After defining the supply model, the demand characteristics, and the user choice model, we need to define the dynamic assignment model focused on the network loading which will be used for our simulation purposes. In this section we define how the demand generation is affected by the user choice, how the demand interacts with fleet vehicles and how we simulate the within-day action of the public transport system.

4.1.- Package dynamic generation

The O-D strategies matrix defines all attractive service for every trip which can be done using the public transport system. When a package p is generated at instant t in the origin centroid c_i and has a destination centroid c_p, the static strategies $E_{c_i}^{c_p}$ allow the definition of the time interval needed for the calculation of formula (3.1). Consider in the previous situation that the last attractive service s_0 departed from the station n associated to the c_i centroid at instant $t_n^{s_0} = t_1$ (see Figure 6). When a new attractive service s departs from the same station at instant t_2 we estimate that new packages p are generated for each destination centroid c_p and their demand volume is calculated by:

$$r_p = \int_{t_1}^{t_2} \delta_{c_i,c_p}(\xi) d\xi = \int_{t_1}^{t_2} d_{c_i,c_p} \cdot \mathrm{P}(\xi) d\xi \qquad (4.1)$$

Each new package p generated is added to the set of packages $\mathcal{P}^{c_i}$ waiting in centroid c_i, so $\mathcal{P}^{c_i} = \mathcal{P}^{c_i} \cup \{p\}$. In this procedure, the *fusion* operation (+) between homogeneous packages is used.

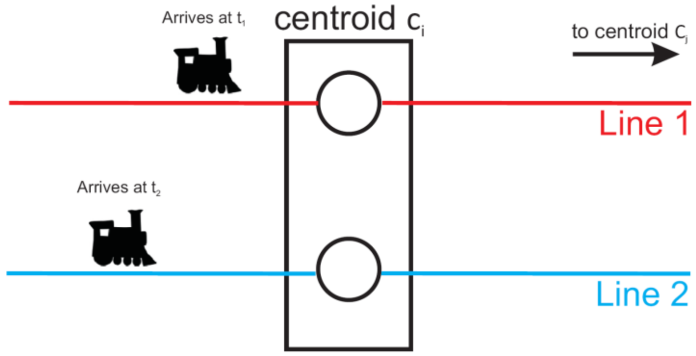

Figure 6: Attractive services concept for package generation in time

4.2.- Boarding and alighting procedures

Boarding mechanism is used before a service departs from a station. In this case, we assume that a set of packages $\mathcal{P}^{c_i}$ are waiting at the station associated with the centroid c_i but there is *no queue priority*. Railway passengers wait at a platform until an attractive service arrives, but there is no priority in the platform queue. Everyone who is waiting tries to get into the service s considered as attractive, but it could happen that because of the service capacity constraint k_s not everyone fits into the vehicle associated with this service. For this reason, a fail-to-board probability parameter π is calculated depending on the residual capacity of the vehicle estimated during the boarding procedure. This parameter represents the proportion of people who can actually get into a vehicle from a station, considering the vehicle capacity constraints.

On the other hand, the alighting mechanism is used when a service arrives at a station. For alight passengers, we define a set of packages $\mathcal{P}^{v_i}$ as those packages which are travelling in the vehicle v_i. Due to the vehicle capacity constraints, the total volume of this set of packages $\mathcal{I}_{v_i} = \sum_{p \in \mathcal{P}^{v_i}} r_p$ must be less than or equal to the vehicle capacity k_{v_i}.

The two mechanisms presented above make use of strategies $E_{c_i}^{c_j}(t)$ coded as a static matrix $E_{c_i}^{c_j}$: when boarding, strategies are needed to determine how demand is generated (demand arises only when it can be served by an attractive service); when alighting, strategies are needed to define some kind of route choice making people get off a vehicle in a station in order to reach their destination by using another service (transferring to another line) or by walking to their destination (finishing the trip).

For simulation purposes, boarding and alighting mechanisms have been coded as algorithms in pseudo-code form (see Algorithm 1 and Algorithm 2). With these algorithms, the normal action of a public transport system can be simulated during a defined time period. The algorithms described show the alighting/boarding procedure under an event defined by (s_i, n_i) with $s_i \in S^{\ell_i}$. Hence, these procedures take place when a vehicle v_i departs from station n_i assigned to a service s_i which serves a line ℓ_i.

Algorithm 1: Vehicle alighting procedure

Data: $\mathcal{P}^{s_i -}_{n_i} \equiv$ set of packages alighting to go on by other route
Data: $\mathcal{P}^{*}_{n_i} \equiv$ set of packages alighting because they arrive at destination

begin

```
/* Alight each package whose movement strategy to reach its destination is
   a different line or direction to those of the actual used service      */
```
$\mathcal{P}^{s_i -}_{n_i} = \{p \in \mathcal{P}^{v_i} : (\ell_i, w_i) \notin E^{c_p}_{c_i}\}$;
```
/* Alight each package which has reach its destination, where c_i has an
   associated station n_i                                                  */
```
$\mathcal{P}^{*}_{n_i} = \{p \in \mathcal{P}^{v_i} : c_p = c_i\}$;
```
/* Estimate number of people alighting the vehicle                        */
```
$\mathcal{D}_{v_i} = \sum_{p \in \mathcal{P}^{s_i -}_{n_i} \cup \mathcal{P}^{*}_{n_i}} r_p$;
```
/* Estimate the vehicle residual capacity                                 */
```
$k^{s_i}_{n_i} = k^{s_i'} - (\mathcal{I}_{v_i} - \mathcal{D}_{v_i})$;
```
/* Remove from the vehicle v_i those packages which have alighted in the
   station n_i                                                             */
```
$\mathcal{P}^{v_i} = \mathcal{P}^{v_i} - \left\{\mathcal{P}^{s_i -}_{n_i} \cup \mathcal{P}^{*}_{n_i}\right\}$;

end

Algorithm 2: Vehicle Boarding procedure

Data: $\mathcal{P}^{c_i} \equiv$ Two types of packages: i) transferred from other lines and ii) generated in the centroid c_i
Data: $\mathcal{P}^{s_i +}_{n_i} \equiv$ set of packages which want to use the s_i service, using the strategies $E^{c_j}_{c_i}$ con $c_j \in \mathcal{C}$. Note $\mathcal{P}^{s_i +}_{n_i} \subseteq \mathcal{P}^{c_i}$

begin

forall $c_j \in \mathcal{C} : \ell_i \in E^{c_j}_{c_i}$ **do**
  Generate the new package p_j with formula (5.1) and $\mathcal{P}^{c_i} = \mathcal{P}^{c_i} \cup \{p_j\}$;
```
/* Packages whose strategy to reach the destination is the line and the
   direction of s_i service                                                */
```
$\mathcal{P}^{s_i +}_{n_i} = \{p \in \mathcal{P}^{c_i} : (\ell_i, w_i) \in E^{c_p}_{c_i}\}$;
```
/* Estimate the potential demand and the proportional factor π            */
```
$\mathcal{U}_{v_i} = \sum_{p \in \mathcal{P}^{s_i +}_{n_i}} r_p$;
$\pi = min\left\{1, \frac{k^{s_i}}{\mathcal{U}_{v_i}}\right\}$;
if $\pi = 1$ **then**
```
  /* No capacity constraints effects                                       */
```
  $\mathcal{P}^{v_i} = \mathcal{P}^{v_i} \cup \left\{\mathcal{P}^{s_i +}_{n_i}\right\}$;
  $\mathcal{P}^{c_i} = \mathcal{P}^{c_i} - \left\{\mathcal{P}^{s_i +}_{n_i}\right\}$;
if $\pi < 1$ **then**
```
  /* With capacity constraints effects                                     */
```
  forall $p \in \mathcal{P}^{s_i +}_{n_i}$ **do**
    $\{p', q\} = \text{Excision}(p, \pi)$;
    $\mathcal{P}^{v_i} = \mathcal{P}^{v_i} \cup \{q\}$;
```
    /* Packages p' wait and are not removed from P^{c_i}                   */
```
  $\mathcal{P}^{c_i} = \mathcal{P}^{c_i} \cup \mathcal{P}^{s_i -}_{n_i}$;

end

4.3.- Discrete event simulation model

As has been previously described, the main objective of this paper is the development of a simulation model based on a dynamic transit assignment model. This simulator is intended to be a public transport system evaluator which simulates the demand response under certain situations. For this purpose, a discrete event simulation model can be easily built by using elements defined in previous sections.

Algorithm 3 shows the pseudo-code that implements a discrete event simulation considering instants t_n^s defined in line services timetables θ^{ℓ} because they are the potential events for system changes. The system state changes by updating the state of vehicles and the state of the queues waiting on the station platforms.

Algorithm 3: Discrete event simulation algorithm

Initialization ;
t_0: start simulation instant ;
$\mathcal{T}$: final simulation instant **while** $T \leq \mathcal{T}$ **do**
  $T = \min_{(n_i,s_i)} \left\{ t_{n_i}^{s_i} : t_{n_i}^{s_i} \text{ not analyzed and there is an effective service} \right\}$;
  $(n_i^{'}, s_i^{'}) = Arg \min_{(n_i,s_i)} \left\{ t_{n_i}^{s_i} : t_{n_i}^{s_i} \text{ not analyzed and there is an effective service} \right\}$;
  Alighting & Boarding procedures for vehicle v_i associated with service $s_i^{'}$ in station $n_i^{'}$;
  Mark $t_{n_i^{'}}^{s_i^{'}}$ as analyzed ;

5.- COMPUTATIONAL EXPERIMENTS

In order to test the applicability of our model some tests have been performed using real data provided by RENFE Cercanías (Regional services of the Spanish national railway company). The main tests described here consist in the simulation of a single day of normal activity (from 5:00 to 00:59) on one of the busiest lines in the Madrid regional railways services, the C-5 Line. In this section we set out both the data employed for the tests and the results obtained with our developed tool.

5.1.- The Madrid regional railways C-5 Line

The C-5 Line, showed in Figure 7, is one of the busiest lines on the Madrid regional railways services since it serves approximately 400,000 people each day. This line has 45.1 kilometers of track and is located southwest of Madrid. It connects the towns of Móstoles, Alcorcón, Fuenlabrada and Leganés with the Madrid central station called Atocha. During a normal day it provides 320 services with an approximate minimum frequency of 10 services per hour (depending on time period), having peak hours with approximately 25 services per hour.

Figure 7: The C-5 Line map (in orange)

The O-D demand matrix for this line has been provided by RENFE and defines demand distribution data between the 23 stations that C-5 Line comprises. The time distribution function is the same for all O-D pairs and has also been provided by RENFE (see Figure 8). The calculation of strategies is very simple for this test since passengers travel along a single line and only have to decide between one direction and the other. For testing approaches, this simplification does not affect the final results because of the application of a generic strategy generation model which estimates the user choice. Our approach allows the simulation model to employ any O-D strategy matrix well defined and generated by any static strategy generation model.

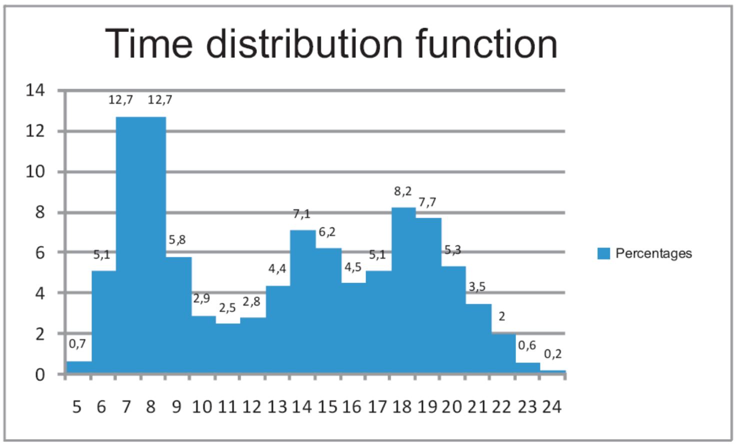

Figure 8: Time distribution function $P(t)$ provided by RENFE

5.2.- Statistical data obtained

A software tool has been developed in MATLAB R2008a for the generation of useful statistical data about the system status. This tool provides a graphical user interface which allows the definition of the data needed for the simulation. It also provides the user with various statistical plots which can be useful to evaluate the demand behaviour under some system states. The statistical plots that our tool gives to the user are related with the following system characteristics:

- *Transport system plot:* This plot is calculated by using counters of how much demand reaches its destination and how much demand is generated and uses the system to travel in each instant t. With these data the service quality in the whole transport system can be measured as the difference between people in and people out.
- *Vehicle plots:* Two different plots related with vehicles are provided to the user. One of them represents the real capacity (i.e. how many people are needed to exceed the vehicle capacity) variation during the simulated period. The other plot shows the variation of the demand volume which travels on a vehicle towards a single centroid destination during the simulated period. This statistic allows the user to identify which services are more or less congested and also to check that our capacity constraints work properly.
- *Station plots:* Station information follows a similar approach to the vehicle information. One plot presented to the user shows how the demand volume of each station queue varies over the simulated time period. This information can also be constrained by selecting demand volume of each queue depending on a destination station. These two statistics allow the operators to detect if demand is served properly or if travellers find complications in performing a trip between two particular stations.

5.3.- Results

Two tests have been carried out by a simulation from 5:00 to 00:59 using real data provided by RENFE and using the C-5 Line as a testing line. The first test case (Case A: Congestion) studies how demand is evaluated when there is congestion and not all the demand can be satisfied. This test shows those examples where system capacity is exceeded by the demand. In the second (Case B: Double capacity), we define double capacity trains to prove that our simulation model, when the same number of services but having more capacity than in Case A are considered, provides a system response where demand can be fully served. Both test cases have been analyzed in order to evaluate which situation can be interpreted by the public transport operators using statistical plots.

For the Test Case A, the plot shown in Figure 9 illustrates that not all the people are served. During the simulated period, over 415 thousand people enter the system and around 340 thousand are fully served. So an operator can conclude that more services are needed to serve all the demand. In Test Case B, during the simulated period, over 415 thousand people enter the system and around 411 thousand are fully served. This test shows the operator that although some extra services are needed, with larger vehicles the demand can be almost fully satisfied (see Figure 10). Although 4 thousand people seem not to be served, this is because a final vehicle is missing and some demand is not satisfied.

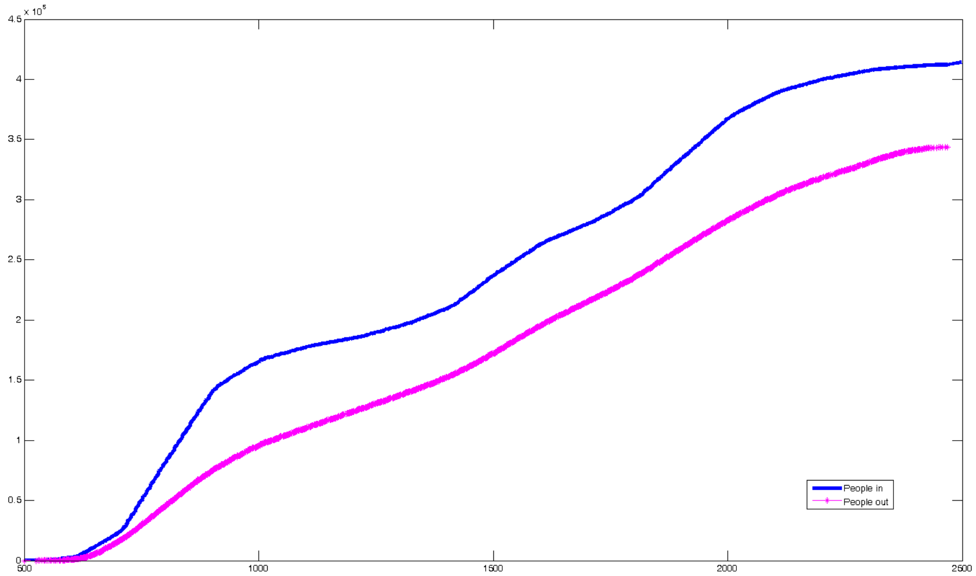

Figure 9: Transport system plot in C-5 Line (Case A: Congestion)

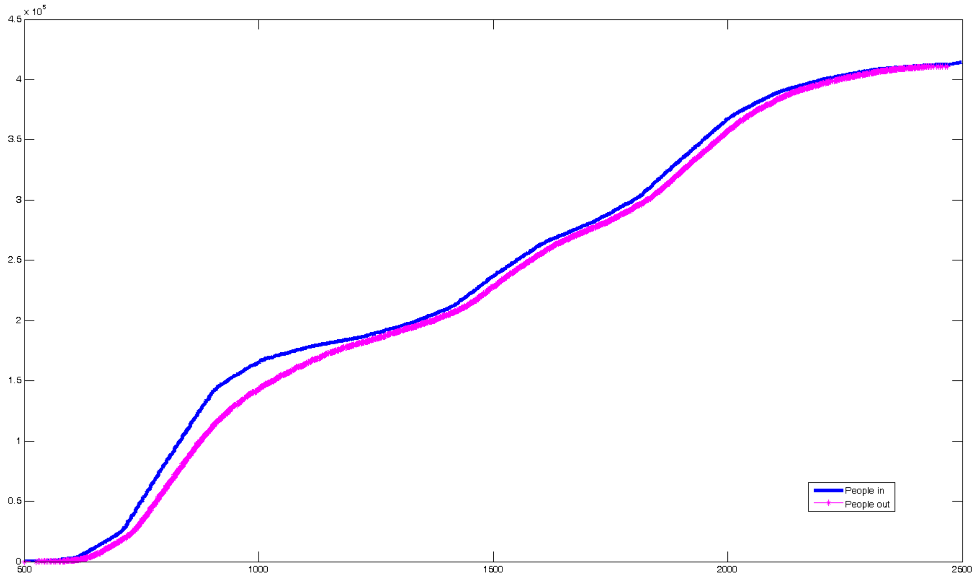

Figure 10: Transport system plot in C-5 Line (Case B: Double capacity)

Some statistical plots are also given to the operator to obtain information about queue evolution. Considering the Atocha station (Madrid's largest station) and the Fuenlabrada station, operators can evaluate the behaviour of the system by using the plots shown in Figure 11 and 12. For the Test Case A (Figure 11), it can be clearly seen that demand which wants to travel to Fuenlabrada is always waiting in Atocha and scheduled services can't serve it. On the other hand, for the Test Case B (Figure 12) the scheduled services can almost fully serve the demand except for peak hours (between 8:00 and 10:00). In fact, the statistical plot obtained has a similar shape to the time distribution function. This indicates that our simulator provides a proper response depending on the inputs.

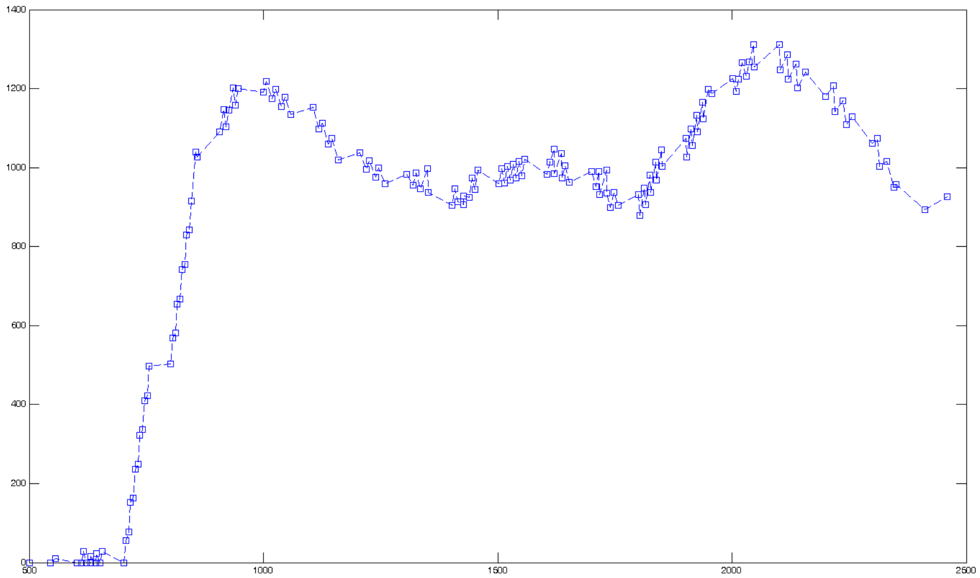

Figure 11: People waiting in Atocha station to travel to Fuenlabrada station (Case A: Congestion)

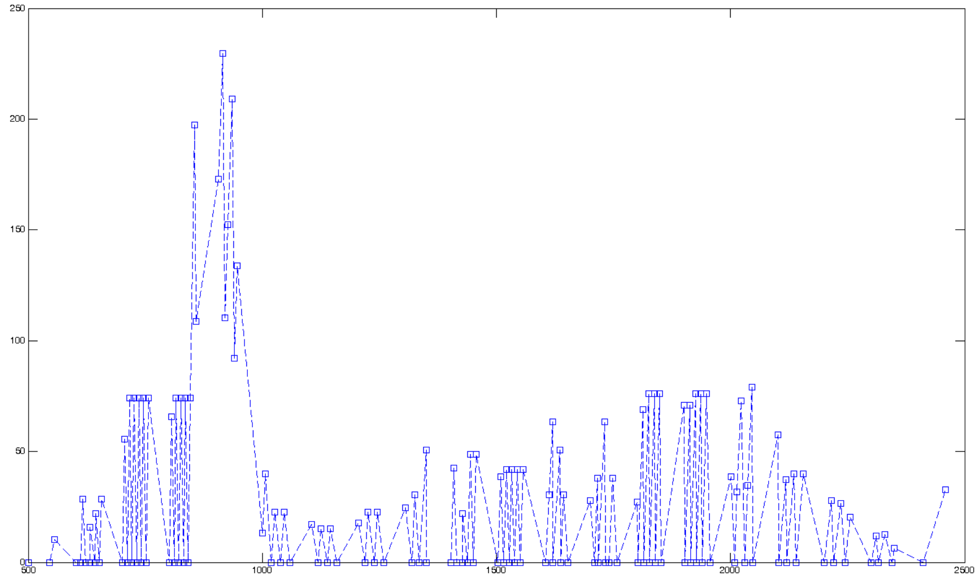

Figure 12: People waiting in Atocha station to travel to Fuenlabrada station (Case B: Double capacity)

The simulated data obtained by the proposed model have been validated by operator experience. The first test case would be similar to a situation in which less than half of the total number of services scheduled are available. The operators pointed out that demand could not be served anyway in this case, so the results are adequate and correspond to real situations which operators have dealt with. The second test would be similar to the actual service schedule which has been designed for serving the demand. In this case, the results obtained are also adequate. Therefore, we can conclude that our simulation model works properly and provides accurate information about the demand behaviour.

Test cases have been run on an Intel Core2Duo E6850 at 3 GHz using Windows XP in its 32 bits version. On a second test stage, test cases have been run on an Intel Core Quad using Windows 7 in its 64 bits version. Computational effort for a simulation is measured in CPU Time (in seconds) and it has two main components: the initialization procedure (in which all data is properly structured and processed to make a simulation) and the simulation procedure itself. The following table shows all the data related to the computational task:

Table 2: Computational effort data for tests

Machine employed	Initialization CPU time	Simulation CPU time
Case A: Core2Duo	204 seconds	22,920 seconds
Case B: Core2Duo	205 seconds	23,110 seconds
Case A: Core Quad	159 seconds	24,820 seconds
Case B: Core Quad	159 seconds	25,160 seconds

After a results analysis we conclude that our model response is good enough to provide accurate simulations. Our simulation model provides an appropriate system response when network conditions (fewer services or double capacity) are changed. Although the computational burden (1 real action hour is simulated in less than 20 minutes) is acceptable for simulation or evaluation purposes, the application of parallel computing or high performance computing should be considered. Finally, the statistical plots provided to the user are a good tool for supporting decisions taken by public transport operators.

6.- CONCLUSIONS AND FUTURE RESEARCH

This paper proposes a dynamic transit passenger assignment model as part of a simulation model for public transport networks, initially designed as part of an incidence management system. The simulation model is based on: i) a mixed supply model with capacity constraint, queue models, and fail-to-board estimations, ii) a static user choice model based on a generic strategy generation model and assuming that passengers use the predefined travel strategies under normal situations, and iii) a dynamic transit assignment model for network loading.

This simulation model has been tested using real data from the C-5 Line (Madrid regional railways) provided by RENFE Cercanias. The two tests performed to check the applicability of this simulation model, have shown that our approach has a good enough response for simulating and evaluating different transport system configurations. Several machine configurations have been employed and the results show that our model can have several operational applications. Statistical plots provided by the developed tool are very useful for the evaluation of public transport system status. However, more computational tests have been scheduled and will show the applicability of our approach to real problems with larger amounts of data.

A dynamic strategy generation model would be an important effort to improve the accuracy of the user choice model, and will be included in later versions of the simulation model. The implementation of this kind of model will provide a powerful and practical simulation system for various applications like the evaluation of new timetables, the analysis of congestion effects over demand strategies or simply to provide accurate demand data to evaluate decisions which can be taken about the service network.

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