DYBUS2: a real-time mesoscopic transit modelling framework

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Summary

✓ Introduction
✓ State-of-the-art
✓ DYBUS2 real-time mesoscopic transit modeling framework
  ▪ logical framework
  ▪ modeling features
✓ Application example
✓ Concluding remarks and future developments
Introduction

APTS (Advanced Public Transportation Systems)

apply telematics technologies in order to improve network performances both from users and operators perspective

real-time short-term prediction of on-board loads
Introduction

Real-time short-term prediction of on-board loads

Two possible approaches:

 ✓ aggregate-statistical or projection methods
   (Tsai et al., 2009; Chen et al., 2011; Wei and Chen, 2012; Jiuran and Bingfeng, 2013)

 ✓ transit network assignment models
   - line-oriented (e.g. frequency-based)
     (Nguyen and Pallottino, 1988; Spiess and Florian, 1989)
   - run-oriented (e.g. schedule-based)
     (Lam and Bell, 2003; Wilson and Nuzzolo, 2004)
     - analytical
       (Papola et al., 2009; Ren and Lam, 2007; Sumalee et al., 2009)
     - simulation-based
       (Nuzzolo et al. 2001, 2012; Wahba and Shalaby 2009, 2014; Cats et al. 2011)

Network assignment models allow to obtain more accurate estimates of on-board loads by
the reproduction of traveller behavior in travel choices, according to current system
functioning and type of information provided.
State-of-the-art
Simulation-based models

Simulation-based models consider the interaction among agents representing single travellers and single transit vehicles.

According to the level of detail in supply and demand modeling, they can be classified into:

- microscopic (micro)
- mesoscopic (meso)
  - demand and/or supply side
Introduction

Mesoscopic models

**Supply**

Representation of single vehicles through aggregated traffic performances

**Demand**

travel behavior passengers represented as individual travelers or packets of travelers
Introduction

Mesoscopic models (advantages)

Despite the greater level of output details of micro-simulation models, the meso-simulation allows to analyze large networks with respect to the limited stretches of the micro-simulation approach.

Mesoscopic models are:

✓ easy-to-apply
✓ computationally simpler
✓ less time-consuming

suitable to be used for

real-time short-term prediction of on-board loads at network level
State-of-the-art
Mesoscopic assignment models for transit network in presence of traveller information

Very limited literature:

- **DYBUS**
  (Nuzzolo et al., 2001; 2012)

- **MILATRAS**
  (Wahba and Shalaby, 2009; 2014)

- **BUSMEZZO**
  (Cats et al., 2011)

<table>
<thead>
<tr>
<th><strong>为主的</strong></th>
<th><strong>主要参数</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>旅行者信息</td>
<td>需求与供应</td>
</tr>
<tr>
<td>运输规划</td>
<td>供应</td>
</tr>
<tr>
<td>客运操作</td>
<td>供应</td>
</tr>
</tbody>
</table>

**Mesoscopic features**

*DYBUS*, *MILATRAS*, and *BUSMEZZO* are primarily oriented to transport planning, which is closely related to the demand and supply of travel services.
DYBUS2

What’s new

Extension of DYBUS family models proposed in Nuzzolo et al. (2001) and developed in Nuzzolo et al., (2012), which allows to take into account:

✓ real-time model use

✓ simulation of travel behaviour in the sphere of real-time information to travellers, by using a travel strategy approach

✓ real-time individual predictive information about on-board crowding
**DYBUS2**

**Logical architecture**

DYBUS2 core module predicts in real time the network performances and the number of on-board passengers for each vehicle at each stop of the transit network.

It includes:

- time-dependent demand generation
- run-oriented network evolution model
- path choice and assignment models
- demand and model parameter updating

![Diagram of DYBUS2 Logical architecture](image)
Mesoscopic time-dependent demand generation

The demand is characterised by times in which users desire start or end their trips (user target times, $TT$):

- Desired Departure Times ($DDT$)
  which represent the times in which users would departure from origin,

- Desired Arrival Times ($DAT$),
  which represent the times in which users would arrive at destination

"Packets" of travelers characterized by the same Origin-Destination pair $OD$ and target time $\tau_{TTi}$ are generated every minute
Mesoscopic run-oriented network evolution model

Transit system operations at time $\tau$ of day $t$ are represented through a diachronic graph $\Omega_{\tau,t}$, which is made of two parts:

- the first representing **consolidated** transit operations up to time $\tau$ of day $t$ (i.e. what happened before time $\tau$)
- the latter representing the **prediction** of transit operations from time $\tau$ to the end of day $t$ (i.e. what is currently expected to happen after time $\tau$)

**Transit network updating** is carried out at fixed steps (e.g. 1 minute) when:

- a traveller packet departs from origin
- a vehicle arrives or departs from a stop

by considering the prediction of vehicle dwelling times at stops and that of vehicle running times between stops obtained by available real-time data (e.g. AVL data or traffic simulators)
DYBUS2

Path choice and assignment models

Modeling features:
- Behavioral assumptions
- Path choice modeling
- Within-day network loading
- Day-to-day learning process
- On-board crowding prediction

Initialization

\[ h_0^{(t)} = H_{t,0} \]

Within-day initialization

- \( \tau, \tau_{END} = \) first and last instant of simulation
- \( \alpha = \alpha_0, \Delta = 1 \text{ min} \)
- \( h_0^{(t)} = 0 \)

Path choice and assignment models

Day-to-day attribute estimation (prior knowledge on day \( t \))

Day-to-day

\[ t = t + 1 \]

Within-day

Transit network initialization (day \( t \))

Transit network updating at time \( \tau \) of day \( t \)

(Diachronic network \( \Omega_\tau \))

Within-day

Anticipated attributes at time \( \tau \) of day \( t \)

\[ x_\tau^{(t)} = X(h_\tau^{(t)}) \]

Anticipated attributes

\[ W_\tau^{(t)} = H_\tau^{(t-1)} \]

Day-to-day

On-board crowding prediction (fixed point)

\[ \text{For each } \tau' \geq \tau \]

Path (at-origin and at-stop) choice and network loading

\[ W_\tau^{(t)} \]

\[ \frac{W_\tau^{(t)} - W_\tau^{(t-1)}}{W_\tau^{(t-1)}} \leq 0 \]

Yes

No

\[ \tau > \tau_{END} \]

\[ \tau = \tau + \Delta \tau \]
Path choice modeling

*Behavioral assumptions (1/5)*

Behavioral assumptions are defined in the context of:

- **unreliable** or stochastic service network with diversion nodes (i.e. nodes where decisions are carried out according to realizations of random events)

- **frequent** travelers (i.e. people that often travel on a given origin-destination pair), equipped with mobile devices that allow them to access *real-time individual predictive information* about routes and relative characteristics (i.e. run arrival times at stops, travel time components and on-board crowding) from the traveler current position to the destination.

\[\downarrow\]

*travelers do not choose, at origin, an entire path until destination, but they use a travel strategy with an adaptive behavior*
Path choice modeling

Behavioral assumptions (2/5)

**optimal travel strategy**

Set of rules that defines a sequence of choices that maximizes the expected travel utility, carried out combining real-time predictive information and past experiences:

✓ the first choice is **at origin**, which includes the departure time and the first boarding stop

✓ the successive choices **during the trip**, at given points of the networks (e.g. stops), where travelers can make adaptive en-route decisions, according to the realization of random events, by using a prefixed decision rule on how better proceed up to the next decision point

A travel strategy can be topologically represented with an **hyperpath** characterized by **diversion nodes** at decision points along the trip.
Path choice modeling

Behavioral assumptions (3/5)

Example of hyperpath

\[\text{hyperpath } K_1: \text{Origin - Stop } A - \text{Line 1 - Stop } C - \text{Destination}\]
\[\text{hyperpath } K_2: \text{Origin - Stop } B - \text{Line 2 - Stop } D - \text{Destination}\]
\[\text{hyperpath } K_3: \text{Origin - Stop } B - \text{Line 3 - Stop } D - \text{Destination}\]
\[\text{hyperpath } K_4: \text{Origin - Stop } B - \text{Line 2 or 3 - Stop } D - \text{Destination}\]
\[\text{hyperpath } K_5: \text{Origin - Stop } A \text{ or } B - \text{Line 1 or 2 - Stop } C \text{ or } D - \text{Destination}\]
\[\text{hyperpath } K_6: \text{Origin - Stop } A \text{ or } B - \text{Line 1 or 3 - Stop } C \text{ or } D - \text{Destination}\]
\[\text{hyperpath } K_7: \text{Origin - Stop } A \text{ or } B - \text{Line 1 or 2 or 3 - Stop } C \text{ or } D - \text{Destination}\]
Path choice modeling

Behavioral assumptions (4/5)

✓ as frequent users on a given Origin-Destination pair $OD$ with target time $\tau_{TTi}$, travelers identify and experience several strategies

✓ in order to find the optimal hyperpath $K^*$ at time $\tau$ of day $t$, travelers compare travel options by associating a subjective utility to each alternative hyperpath $K$

✓ the subjective utility associated to hyperpath $K$ is function of the experienced utilities of the single paths within $K$, adaptively chosen in previous days

✓ due to the stochastic network, the experienced hyperpath utility is a random variable and the comparison among hyperpaths can be carried out according the Decision Theory in uncertainty context:
  ▪ by comparing the subjective expected (or non-expected) utilities
  ▪ by choosing that of maximum subjective expected utility
Path choice modeling

Behavioral assumptions (5/5)

Given the optimal hyperpath $K^*$, decision rules at diversion nodes are required:

✓ when travelers reach a decision point $i$, (sub)hyperpaths $k_{i,l}$ having the root in the diversion node $i$ and incorporating the diversion link $l$ are dynamically generated according to realizations of random events and to real-time information

✓ travelers compare the anticipated utilities of the available (sub)hyperpaths, choosing the one of maximum anticipated utility

✓ anticipated utilities are obtained through a learning process combining the values of path attributes real-time predicted by the information system and the expected values of the same attributes deriving from previous experiences
### Path choice modeling

**Modeling optimal hyperpath $K^*$ choice (1/4)**

<table>
<thead>
<tr>
<th>compensatory</th>
<th>non-compensatory</th>
<th>hyperpath choice set generation</th>
<th>hyperpath choice</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$p^t[K^*/o]$</td>
<td>$o$</td>
</tr>
</tbody>
</table>

Semi-compensatory two-stage choice process:

1. non-compensatory rule-based path choice set generation procedure
2. compensatory hyperpath choice model formalized within the Random Utility framework
Path choice modeling

Modeling optimal hyperpath K* choice (2/4)

Given the OD pair and target time $\tau_{TTi}$, the choice set of alternative hyperpaths from origin $O$, $O$, is obtained by:

1. generating single OD paths on the basis of:
   - logical constraints
     (e.g. avoid loops, as well as successive boarding of the same run or the use of opposite lines).
   - behavioral constraints
     (e.g. eliminate unrealistic alternatives in terms of maximum values of attributes, such as number of transfers, transfer time, schedule delay, access and egress times).

2. combining the above residual paths into hyperpaths
   (overlapping rules)
Path choice modeling

Modeling optimal hyperpath $K^*$ choice (3/4)

Given the time $\tau$ of day $t$, the probability of choosing hyperpath $K^*$ can be written as:

$$ p^{t \ K^* \ O} = \text{prob}[ \text{EU}_{K^*}^t > \text{EU}_K^t ] $$

where $K$, $K^*$; $K^*$, $K^* \ O$

where the (subjective) expected utility of traveler $u$, $\text{EU}_{K,u}^t$, is given by:

$$ \text{EU}_{K,u}^t = \text{EV}_{K,u}^t + h_{K,u}^t $$

where:

- $\text{EV}_{K,u}^t$ is the systematic expected utility relative to all travelers $u$, which is computed by the modeler; it can be assumed as the average value of $\text{EU}_{K,u}^t$
- $h_{K,u}^t$ is the random residual, which is the deviation of $\text{EU}_{K,u}^t$ from the systematic utility value; it takes into account traveller’s cognitive process errors, traveller’s preference variations, as well as modeler approximations.
Path choice modeling

Modeling optimal hyperpath $K^*$ choice (4/4)

The systematic expected utility $EV_{K^*}^t$ can be written as:

$$EV_{K^*}^t = \sum_{w=1}^{M} p_{K^*[w]} \times TV_{K^*,w}^t$$

where:

- $TV_{K^*,w}^t$ is the utility of path $w$ in $K^*$ at time $\tau$ of day $t$, which has been experienced in previous days.
- $p_{K^*,u}[w]$ is the percentage of use of path $w$ in $K^*$ in previous days.

$$E(V_{K^*}^t) = \sum_{w=1}^{M} p_{K^*[w]} \times TV_{K^*,w}^t$$
Path choice modeling

Modeling (sub)hyperpath $k$ choice (1/2)

Given the optimal hyperpath $K^*$, the choice of (sub)hyperpath $k_{i,j}$ of $K^*$ is carried out comparing the anticipated utilities of possible alternatives, given by:

$$AU_{k_{i,j}}^t = AV_{k_{i,j}}^t + e_{k_{i,j}}^t$$

where:

$AV_{k_{i,j}}^t$ is the systematic anticipated utility

$e_{k_{i,j}}^t$ is the random residual
Path choice modeling

Modeling (sub)hyperpath k choice (2/2)

The anticipated systematic utilities of the $G$ paths belonging to (sub)hyperpath $k_{i,l}$ can be written as:

$$AV_{k_{i,l}}^t = \frac{1}{G} \sum_{w=1}^{G} p[w] \times AV_{w}^t$$

where:

- $p[w]$ is the percentage of use of path $w$ within (sub)hyper-path $k_{i,l}$ in previous days
- $AV_{w}^t$ is the systematic utility of path $w$ at time $\tau$ of day $t$, given by:

$$AV_{w}^t = \sum_{j=1}^{J} b_j \times AX_{w,j}^t$$

in which: $AX_{w,j}^t$ are the anticipated path attributes

$j$ are model parameters
Path choice modeling

Anticipated attributes estimation

The generic attribute $j$ anticipated at time $\tau$ of day $t$, $AX_{w,j}^t$, can be obtained as:

$$AX_{w,j}^t = \chi FX_{w,j}^t + (1 - \chi) EX_{w,j}^{t-1}$$

where

- $FX_{w,j}^t$ is the attribute provided by the real-time information system on day $t$
- $EX_{w,j}^{t-1}$ is the attribute expected on day $t-1$
- $\chi \in ]0,1]$ is the weight given by the traveler to the information provided
Path choice modeling

Modeling (at-stop) diversion link choice (1/2)

The choice of the boarding vehicle is simulated by a

*sequential binary choice mechanism*

\[ \downarrow \]

When a run \( r \) belonging to the (sub)hyperpath \( k_{s,r} \) arrives at stop \( s \), the traveler chooses to board run \( r \) if:

\[
AU_{k_{s,r}} > AU_{k'_{s,l}}, \quad k'_{s,l}, k_{s,r}, k_{s,l} \in K^*
\]

where:

- \( AU_{k_{s,r}} \) is the anticipated utility associated to (sub)hyperpath \( k \) incorporating run \( r \)
- \( AU_{k'_{s,l}} \) is the anticipated utility associated to (sub)hyperpath \( k' \) incorporating diversion link \( l \) representing the waiting at stop \( s \) for successive arrivals
Path choice modeling

Modeling (at-stop) diversion link choice (2/2)

Example of

sequential binary choice mechanism

at stop $s$ for the arriving run $r$
On-board crowding prediction

Given a generic time $\tau$, the problem of providing real-time information about on-board crowding requires the simulation of the entire transit system from time $\tau$ to the end of the day.

$$h_*^t = \_^t \times P^t [ U^t ( X^t ( h_*^t ))] \times d$$

It requires the solution of a fixed-point problem because of the dependence of on-board loads $h$ from path choice probabilities $P$, which in turn depend also on on-board loads $h$ themselves.
Application

Test Network

Typical workday (7:00-10:00)

✓ 11 zones
✓ 11 lines
✓ 245 runs
### Application

**Path choice model parameters (Logit)**

<table>
<thead>
<tr>
<th>attribute</th>
<th>units</th>
<th>parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>schedule delay</td>
<td>min⁻¹</td>
<td>-0.45</td>
</tr>
<tr>
<td>access time</td>
<td>min⁻¹</td>
<td>-0.11</td>
</tr>
<tr>
<td>waiting time</td>
<td>min⁻¹</td>
<td>-0.30</td>
</tr>
<tr>
<td>on-board time</td>
<td>min⁻¹</td>
<td>-0.09</td>
</tr>
<tr>
<td>transfer time</td>
<td>min⁻¹</td>
<td>-0.14</td>
</tr>
<tr>
<td>n. of transfers</td>
<td></td>
<td>-0.58</td>
</tr>
<tr>
<td>on-board crowding</td>
<td></td>
<td>-1.31</td>
</tr>
<tr>
<td>time spent at stop</td>
<td>min⁻¹</td>
<td>+0.24</td>
</tr>
</tbody>
</table>
Application

Example of short-term on-board prediction

Different scopes of real-time predictions:

- < 30 min ➔ traveller information
- > 30 min ➔ operations control
Application

Simulation results

Effectiveness of providing real-time predictive information about on-board crowding

<table>
<thead>
<tr>
<th>crowding scenario</th>
<th>information about on-board loads</th>
<th>total waiting time (hours)</th>
<th>total on-board time (hours)</th>
<th>total transfer time (hours)</th>
<th>total travel time (hours)</th>
<th>total early schedule delay (hours)</th>
<th>total late schedule delay (hours)</th>
<th>avg traveller (dis)utility</th>
<th>avg on-board load at stop (pass)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOW</td>
<td>WITH</td>
<td>123.1</td>
<td>870.2</td>
<td>5.5</td>
<td>993.3</td>
<td>132.1</td>
<td>53.3</td>
<td>0.0865</td>
<td>24.9</td>
</tr>
<tr>
<td></td>
<td>WITHOUT</td>
<td>134.2</td>
<td>871.9</td>
<td>6.1</td>
<td>1006.1</td>
<td>116.1</td>
<td>72.0</td>
<td>0.0899</td>
<td>25.4</td>
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<tr>
<td></td>
<td>DIFF (%)</td>
<td>-8.3%</td>
<td>-0.2%</td>
<td>-9.8%</td>
<td>-1.3%</td>
<td>13.7%</td>
<td>-26.1%</td>
<td>-3.8%</td>
<td>-1.8%</td>
</tr>
<tr>
<td>HIGH</td>
<td>WITH</td>
<td>331.3</td>
<td>1 774.8</td>
<td>15.6</td>
<td>2 106.1</td>
<td>256.6</td>
<td>208.2</td>
<td>0.1038</td>
<td>41.1</td>
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<tr>
<td></td>
<td>WITHOUT</td>
<td>366.8</td>
<td>1 774.9</td>
<td>18.3</td>
<td>2 141.7</td>
<td>224.3</td>
<td>274.0</td>
<td>0.1112</td>
<td>41.3</td>
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<tr>
<td></td>
<td>DIFF (%)</td>
<td>-9.7%</td>
<td>0.0%</td>
<td>-14.8%</td>
<td>-1.7%</td>
<td>14.4%</td>
<td>-24.0%</td>
<td>-6.6%</td>
<td>-0.5%</td>
</tr>
</tbody>
</table>
Concluding remarks

✓ mesoscopic models are easy-to-apply, computationally simpler and less time-consuming to obtain the required output details

✓ in order to consider service network unreliability, path choice has to be formalised in the context of a travel strategy in which travellers choose on the basis of both their prior knowledge and real-time individual predictive information on travel time components and crowding at single vehicle level.

✓ providing real-time information about on-board crowding implies the solution of a fixed-point problem

✓ application example shows the effectiveness of providing real-time predictive information about on-board crowding
Further developments

Further research activities in this field are in progress.

They mainly concern:

✔ additional investigations on experimental evidences
   including new applications on large-networks

✔ further calibrations of path choice models
   extending the individual path choice modelling to the personal parameter estimation for the use in recommended information systems

✔ the development of more efficient algorithms for both path choice set generation and fixed-point solution
   connected to the prediction of on-board crowding that an information system has to provide
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