Modeling the multimodal mass transit system and its passengers

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Abstract

SNCF Transilien is a major operator of Paris suburban trains, which witnessed an increase by 30% of its daily passengers over the last decade. Congestion arising from such a growth has added every year more pressure and more complexity to the operations of the transportation system. In this paper, we present a three-step method to comprehend and to model a whole multimodal mass transit system, including its passengers' behavior. First, we develop a simulation tool to model the multimodal system on a restricted geographic scope, based on complex systems modeling. In parallel, we study the passengers' behavior through an on-site enquiry; we take a particular interest in their behavior while facing disturbances compared to normal situation. Finally, the results of the behavioral approach will be integrated into the simulation prototype using a multi-agent model. The resulting tool will allow Transilien operators to anticipate passenger flows in case of disturbances.

1. Introduction

In 2014, more than half of the world population was living in cities[1]. This ratio is expected to reach 70% by 2050. Therefore, more and more city dwellers are likely to move within ever-growing urban areas. The region of Paris faces a similar pattern. For instance, SNCF Transilien, one of the major suburban train operators in Paris, experienced a 30% increase of ridership over the last decade. Yet, existing infrastructure and resources can hardly keep up with such a rising demand. Multimodal solutions can help sustain urban mobility while matching more effectively existing transport modes with users' needs. Hence, a true incentive lies in understanding the passengers' behavior in transport systems.

This paper will describe one approach to improve the knowledge of such behavior within a mass transit system. In a nutshell, the combination of a transport representation with passenger interactions fosters a simulation tool for the sake of evaluating mobility scenarios. Nonetheless, the feasibility of such simulation over a large territory is bounded up with the scalability of its underlying model.

Traditionally, the railway system is tackled with physical and logical graph representations. As a physical graph, arcs and nodes hold the physical connectivity of rail tracks. Trains travel through the physical graph from station to station. As multiple transport lines sometimes use the same tracks, it means the infrastructure may be shared between trains from different origins and destinations. The logical graph holds the path to go from one station to another, depending on the available transport services.

Adding passengers' behavior to the overall model (waiting time, modal choice, rerouting) and real origin-destination improve the quality of the prediction (Van der Hurk, 2010). Chorus (2012, p. 100) underlines that "there is definitely more 'behavior' in the average travel demand model today, than there was ten to fifteen years ago and this is, on average, a good thing." Some models exist to predict human behavior in

[1] Source : world urbanization prospects, by the United Nations Organization

the field of transport. They are based on economic theories and more often on the artificial idea that human is rather rational and a perfect utility maximizer. Chorus (2012) highlights some challenges for travel choice. It is complex and needs a special kind of modeling that must overcome the gap between conventional and behavior-inspired demand models. To achieve this goal, there must be a trade-off between added behavioral realism and lost tractability, especially in large scale models. Existing research, focused especially on mode choice or on route choice from the driver point of view, is a good base to go further.

Following a brief literature overview of the domain, the article provides a description of the methodology as well as insights of modeling. Then, first simulation results derived from the SNCF Transilien use case are presented herein and finally, future work is proposed.

2. State of Art

Fixed-block signaling (Pearson, L. V. 1973) is a traditional system in railway traffic that has been widely used on modern railways for more than a century. The Fixed-block Signaling scheme divides railway line into blocks. The length of blocks depends on maximum speed, braking rate and number of signaling aspects. At any time, one block of track is only occupied by no more than one train. And the train movement is controlled by the signaling light. In addition, most of rail transport operators use a scheduling procedure via timetable (Railway Timetable and Traffic, 2008). Scheduling means to coordinate the train paths ordered by competing train operating companies.

Regarding the passengers' behavior, the field of understanding travel choices relies a lot on economics. Research with that approach uses concepts like bounded rationality, inertia, and uncertainty, and considers the situation of making a travel choice as an ill-defined problem (Newell & Simon, 1972). Those situations do not have a single optimal solution but can lead to several equally correct solutions (Fiorenzo-Catalano & al., 2003). Moreover, alternatives and consequences of the choice are only partly known. Research has tried to identify the determinants which influence the set of considered alternatives (Johnson & Raab, 2003), and to explain the chosen one (Bonsall, 2004). Last & Manz (2003) list 3 main factors:

- The system: availability of alternatives, accessibility, level of service, fare,
- The decision-maker: travelers' characteristics such as socio-demographic characteristics (e.g. Zhang & al., 2012), skills (Majumder & al., 2013), habits, experience (Bonsall & Palmer, 1999), knowledge, preferences,
- The situation: characteristics of the trip (purpose, length, direction...) (Peirce & Lappin, 2004).

To these 3 factors, one can be added, the information. The moment (Polak & Jones, 1993), but also the content and the form of the information (Bonsall & Palmer, 1999), influence the decision-maker in modifying his or her perception of the situation, and his or her state of mind.

Integrating passengers' behavior within a simulation model implies people modeling; a literature search on the subject reveals that people, as crowds or groups, may be simulated in a variety of ways, which mostly depend on the purpose. The landscape of simulation models usually shows two main categories: the macroscopic models and the microscopic ones. The macroscopic approach generalizes the individuals' behavior as a whole resulting with everyone acting the exact same way. On the other hand, microscopic models confer to individuals an autonomous behavior but at price of complexity and higher computational burden. On a microscopic scale, behavioral models such as social force models (Helbing & al., 1995) try to take social and psychological weights into account. On either macroscopic or microscopic scales, network models identify the individual's environment as a logical network made of walkways and intersections. Finally, hybrid models are an attempt to combine the advantages of both

microscopic and macroscopic models, that means simulating individual level interactions while keeping a low computation time. This is usually achieved at the price of precision, aggregating individuals or partitioning space (Xiong & al, 2010).

Macroscopic models proceed by replacing passengers' decisional process with the behavior of fluids or gases. A realistic approach implies interactions on an individual's scale through an agent modeling; the agent's function is then host of the decisional process (Shoham & Leyton-Brown, 2010).

3. Methodology

First, we model the railway system at a mesoscopic scale in a simulation tool. Then, we approximate the multimodal network at a macroscopic level. Finally, we model passenger flows through a behavioral approach captured with a precise on-site enquiry. The results of the behavioral approach are then integrated into the simulation prototype constituted of a Bayesian network, which simulates simple behavior as an inference process (Hy & al. 2004), and a multi-agent system to represent passengers.

a. Railway model

The railway model is made of a physical network, an operator and rolling stocks. The network consists in railways, light signals, rail switches and stop points. Rolling stocks aim to follow the transportation plan given by the operator, while guaranteeing safety and structure constraints. More precisely, a train has to check the state of a signal it encounters to ensure its security distance with a further train (the *Signaling block system*): it implies interactions from the rolling stocks on another. For security purpose, a train has to close completely its doors to carry on its mission. Boarding and alighting passenger flows can block these doors, preventing the vehicle to start again; it implies an interaction between the passengers and the rolling stocks. Finally, the operator is in charge of the whole network management, starting with the planning and the information given to the customers. From this base of information, passengers will be able to elaborate a strategy to reach their destination point.

Because of the large amount of people using transportation networks, we did not consider passengers through a microscopic model. Therefore, as passengers' behavior is a main part of our study, a macroscopic approach was not appropriate either. Consequently, we opted for a hybrid model called "mesoscopic" implemented through a multi-agent system.

b. Behavioral approach

The aim of the behavioral approach is to identify a range of explanatory variables that influence the evaluation and the choice of a travel alternative, such as the characteristics of the decision-maker, the situation, and the transport system. The used methodology relies on observed choices made by a sample of public transport users. Although transportation has a strong tradition of using stated preference data in behavioral studies (Emmerink & al., 1996), revealed preference methods have showed their external validity and credibility (Chorus, 2012 ; Bonsall & Palmer, 1999). The protocol includes three steps. First, 28 semi-directive interviews were conducted with different types of users (daily, occasionally, tourists). Then two questionnaires were respectively administrated to 185 and 38 of the 185 users of the studied lines. Those two questionnaires were complementary. The first one aims at characterizing the decision-maker and his or her mobility pattern in normal and disturbed situation. The second one aims at measuring the link between a special lived situation and the behavior.

c. Passengers' behavior modeling

A passenger is an individual going from one place, its origin, to another, its destination. He has a class (determined through the behavioral approach) that will help determining its behavior if he encounters a disturbance while traveling. In our hybrid level multi-agent system, each agent is an aggregation of all

passengers in the same place (same station or train), sharing an identical class, and heading to the exact same destination (exit station). Its actions are the result of its agent function, which is based, as previously stated, on a Bayesian network.

We are considering four levels of disturbance corresponding to passengers' point of view: minor disturbance, average disturbance, major disturbance and extreme disturbance. Each of them is a reflection of the disturbance estimated duration, going from fifteen minutes to more than one hour. While waiting for a train, agents may receive an indication on the level of the current disturbance, if any. This is an input of the implemented Bayesian network that holds the agent decisional process. Other inputs are the direction (i.e. is the agent going from home or to home) and the class. According to inputs, some actions may or not be initiated by the agent. *Waiting, canceling the travel, finding a new path* or a *new destination* are actions that may only occurs when the agent is considering the situation as disturbed.

Prior to the simulation is the affectation process. During this stage, passengers and thus, agents, will be initialized and distributed all over the transport network. Depending on the period, passenger journey and travel purposes are different, resulting in variable amount of people and different distribution of classes.

4. Instantiation and experiments

In our study, we selected the railway section that goes through the train station of Versailles-Chantiers, in the Yvelines department, west of Paris. We selected this part of the Transilien network as it holds several interesting characteristics, among them:

- The city of Versailles is served by three other stations: Versailles-Rive Gauche, Versailles-Rive Droite and Porchefontaine. One may find multiple ways to go from one station to another, or to go away from Versailles, using the bus transportation network or to walk;
- Several suburban rail lines are serving Versailles-Chantiers: Line U, toward La Defense, Line N, toward Paris – Montparnasse, and RER C, serving multiple stations throughout the French capital.

This specific disposition of lines and stations allows passengers to engage specific behavior, such as line or even modal shifting, at different points of their trip, in particular in the event of disturbances.

a. Transportation network instantiation

We retrieved data from SNCF Transilien to build its physical infrastructure (signalization, railway switches, stations…) and to create its global transportation plan. The metro line has been reproduced thanks to distances and speeds combination based on open data. Due to its regularity in the peak-time period, the metro line has been planned through a constant frequency. Whereas railway lines are submitted to system-dependant constraints, metros can circulate without restriction on their network. It means that their transportation plan is granted to be followed even when it is overloaded. The next versions are prepared to receive GTFS-based data.

b. Experimental results

First experiments aim at validating the simulation from an operational point of view, without including the behavioral approach results. Then, first results relate to this specific perimeter restricted to the three suburban's rail lines and one metro line, on a one-hour peak-time period (time step: 10 seconds). It represents 100 trains (and about thirteen metros) and 100000 passengers (with a passive behavior for the first tests).

Two incident scenarios are considered: cut off track for one hour, and longer stopping time at some station (10 to 20 minutes).

	Computation time	Number of trains impacted	Average delay on impacted trains
Closed track (1 line, 1h)	20’	3	-
Stop time +10’	20’	3	6 to 7’ per train
Stop time + 20’	20’	4	15 to 17’ per train

Table 1 First experimental results of simulation on incident scenarios

These preliminary results emphasize that even a simple event is likely to be propagated in space and time in the network. Indeed, we noted that these simulations were continuously deviating from the nominal state along the time window that we considered. As the information given to the passengers has been updated, we observed changes in passengers’ routing preferences, which implies a delayed impact on other lines. This tends to show the difficulties to predict the whole system behaviour and hence, to prove the legitimacy to consider the transportation network as a complex system. Further computations have to be carried out to tackle bigger and bigger scope (in space and time). This will allow us to capture efficiently the inner complexity of such a system with the addition, in the next step, of the passengers’ active behavior.

5. Conclusion and outlook

In this paper, we presented a methodology to model and to simulate the mass transit system in Paris suburban area, including passengers’ behavior. We drew inspiration from the literature review to set up the behavioral approach, but we had to adapt it to our specific context, especially regarding the disturbed situation. The complex system approach tackles scalability issue with a multi-scale integration of passenger’s behavior within a mesoscopic model. Nonetheless, we still need to improve performances to consider a real-time use. SNCF Transilien operations managers showed an interest in this tool. In the next few months, experiments will be conducted to improve models and performances for the sake of industrialization.

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