A simulation-based approach to quantifying resilience indicators in a mass transportation system

Kpotissan Adjetey-Bahun
Régie autonome des transports parisiens (RATP), France
kpotissan.adjetey-bahun@ratp.fr

Babiga Birregah
Université de Technologie de Troyes (UTT), UMR 6281, CNRS, France
babiga.birregah@utt.fr

Eric Châtelet
UTT, UMR 6281, CNRS,France
eric.chatelet@utt.fr

Jean-Luc Planchet
RATP, France
jean-luc.planchet@ratp.fr

Edgar Laurens-Fonseca
RATP, France
edgar.laurens-fonseca@ratp.fr

ABSTRACT

A simulation-based model used to measure resilience indicators of the railway transportation system is presented. This model is tested through a perturbation scenario: the inoperability of a track which links two stations in the system. The performance of the system is modelled through two indicators: (a) the number of passengers that reach their destination and (b) the total delay of passengers after a serious perturbation. The number of passengers within a given station at a given time is considered as early warning in the model.

Furthermore, a crisis management plan has been simulated for this perturbation scenario in order to help the system to recover quickly from this perturbation. This crisis management plan emphasizes the role and the importance of the proposed indicators when managing crises.

Keywords

Mass transportation system, railway, resilience, indicators.

1- INTRODUCTION

Our societies depend increasingly on critical infrastructure, i.e. infrastructure that if disrupted would have serious impact on well-being, health, safety of citizens and/or the economy of a region, (Rinaldi et al. 2001). Among this critical infrastructure, one can mention the power supply network, the telecommunications network, transportation systems etc. In order to be efficient, such infrastructure is more and more interdependent. These interdependencies make perturbation in some components of critical infrastructure very difficult to manage (Rinaldi et al. 2001, Zio and Sansavini 2011). In spite of the effort one can invest in reinforcing components' weakness with respect to a large number of threats, it is unrealistic to think that one can cover all types of threats by fully preventing their occurrence and, in the worst case, by finding for each one the appropriate responses under the constraints related to their missions. Therefore there is a real need to understand how, in times of crisis, the system can combines its own resources and the external resources that can be mobilized to ensure business continuity. The concept of resilience has been introduced to measure not only the system's ability to absorb perturbations, but also its ability to recover from perturbations quickly. Hence, resilience is the ability of a system to 'bounce back' to a desired performance state (Barker et al. 2013, Bruneau et al. 2003).

Several definitions of resilience can be found in the literature. For an exhaustive list of definitions, one can refer to (Francis and Bekera 2014). The definition used in this work is based on the model used in the paper of (Bruneau et al. 2003). They define a resilient system as the one that reduces: (a) failure probabilities, (b) consequences from failures, in terms of casualties, damage, and negative economic and social consequences and

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(c) recovery time. Our work mainly deals with the recovery time. They also give four characteristics of a resilient system as described in Figure 1 where $Q(t)$ represents the performance of the system: robustness, redundancy, resourcefulness and rapidity. These characteristics are not easy to quantify. However some authors (Mezzou et al. 2011, Zobel 2011) try to give some relationships between them.

The aim of this paper is to propose performance indicators of a railway transportation system under external perturbation which can help a simulation-based quantification of the resilience of a mass transportation network. Among these indicators one can mention the number of passengers that reach their destination, the total delay of passengers, the cost due to a perturbation, the impact of a perturbation on the environment, etc. This paper presents the first two indicators based on passenger flow simulation.

Almost all resilience indicators of transportation system in the literature focus on the topological and connectivity aspects of transportation system network. But an efficient study of transportation system resilience must take into account the organisational and operational aspects of transportation systems (Reggiani 2013). To take into account these aspects we propose a model which encompasses, beyond topological aspects, the simulation of the management of train lines, the modelling of the operation of trains on each line and the computation of passenger's path within the network. There is also in the literature a lack of time dependent resilience indicators of transportation system. In our model, the time at which the perturbation occurs can significantly impact the proposed indicators. Another time dependent parameter of our model is the recovery time. The total delay of passengers to reach their destination explicitly encompasses time needed to recover from a perturbation.
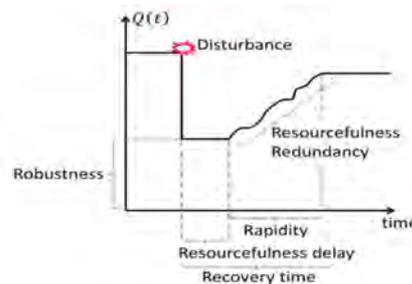

Figure 1. Contribution of Robustness, Redundancy, Resourcefulness and Rapidity to the performance of a system.

The remainder of the paper is organized as follows. Section 2 presents the general model of the mass transportation system which is used for our simulation. A perturbation scenario and its simulation are presented in section 3. In section 4, crisis management plans for this perturbation scenario are modelled and compared. We end this paper by conclusion and perspectives in section 5.

2- THE MODEL

This section presents the proposed model which is a time dependent simulation model to quantify a railway transportation system's resilience indicators.

Let $G = (V, A, W)$ be a digraph where V is a set of nodes representing all stations in the railway transportation system under study. $A \subset V^2$ is a set of arcs of the model which represent tracks between two nodes. $(i, j) \in A$ if, and only if, there is a track linking two stations from station i to station j. W is a set of weights representing the travel time for each arc. With the set of arc V one defines the set of train lines as a subset of the set of paths in G such that each arc $(i, j) \in A$ belongs to exactly one railway line. Even though the set of lines shares cyber-physical interdependencies, each line, normal operating mode, is operated independently from others.

To simulate the flow of passengers within the network during a normal operating activity our model requires the input data listed below:

- For each hour, the number of passengers that enter the system through a node (station).
  Each passenger in the system has his destination node to allow the model to compute his path when he enters the system. At this stage of the work, we assume that passengers take the shortest path in terms of time to reach their destination.
- For each station where passengers can make connection with railway lines, the connecting time between each pair of railway lines.
  This connecting time depends on the lines, the design of the station under consideration and the number of passengers at that station. It can also depend on the fact that it is a rush hour or not.
- The travel time $w_{ij} \in W$ from station i to j. This travel time through each link encompasses the time

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passengers need for boarding and getting off the train. It thus also depends on the period of time.

With the above-mentioned data, the operation of trains on each line of the system is simulated during normal operation and also with perturbation scenarios. Each train in the system has its capacity. That is the maximum number of passengers it can receive. When this number is reached, the train cannot receive any more passengers. Each iteration in the simulation process corresponds to a period of time.

The proposed simulation engine encompasses three main units:

- MySQL database was designed to store the input data listed above
- a Graphical User Interface (GUI) is used to set up some parameters of the simulation like the duration of the simulation, the time step of the simulation, the time the perturbation begins and its duration, etc.
- a traffic simulator, which stimulates the evolution of passengers in the nodes and the links of the network,
- a scenario generators, which computes consequences derived from perturbations and countermeasures.

The output of the model is the performance indicators described in section 1, i.e. the number of passengers that reach their destination and the total delay of passengers. The model is developed in C# with Visual Studio 2012.

3- MODELLING PERTURBATION SCENARIO AND SIMULATION

The model presented in the section 2 allows us to simulate a set of perturbation consequences that could affect a mass transportation network in large cities. The simulation process takes into account perturbations modelled through their consequences on the system, such as the reduction of the capacity of trains, the increase of travel time along a line, the interoperability of arcs, etc.

The mass railway transportation system that will be considered in this work is a part of Paris railway transportation system. It is composed of 360 stations and 850 tracks (i.e. $|V| = 360$ and $|A| = 850$). We have 18 lines within this system. All data described in section 2 are obtained from datasets provided by the transportation operator. For the number of passengers that enter in the system and their destination station, the operator gets them by a survey among passengers. We choose to simulate perturbations on a line which covers more than 7% of the daily traffic of the whole system.

The normal operation of the system modelled (i.e. without any perturbation scenario) shows mean passengers' delay of about 7 minutes for each passenger. The passengers' delay is obtained by computing for each passenger, the difference between the total time spent within the network until he gets out of the network and an ideal time computed for the passenger's path. To compute the ideal time for each path in the network, only the travel time along the links and the connecting times of this path during normal operation of the system are taken into consideration. Thus, the passengers' delay obtained for normal operation is the average of the sum of time spent by passengers when waiting for the train on a station platform.

For the perturbation scenario studied and presented previously, the indicator that consists of computing the number of passengers that reach their destination is not relevant, since the scenario introduced in the present paper doesn't involve dead and/or injured passengers. Thus at the end of the simulation, all passengers reach their destination station. Further work will be devoted on this aspect by injecting disaster perturbation scenario. Passenger behaviour that consists of leaving the system is not yet taken into consideration.

At the level of a station, a measure that can be considered in our study is the number of passengers at that station. This measure can be seen as a weak signal and thus helps crisis managers to set up a management plan if the value of this measure exceeds a given threshold.

Let s be one of nodes that are incident to the arcs we make inoperable for the perturbation and t the time. We define $P_s(t)$ as the performance indicator at station s relative to passenger load:

$$P_s(t) = 1 - \frac{\alpha_{s,d}(t) - \alpha_s(t)}{L_s(t) - \alpha_s(t)}$$

Where $L_s(t)$ is the passenger load at station s the transportation operator can cope with, $\alpha_{s,d}(t)$ the passenger load at station s during the perturbation and $\alpha_s(t)$, the passenger load at station s during normal operation of the system.

Figure 2 shows the curve of $P_s(t)$ for a scenario in which the perturbation begins at 7.00 am and ends at 9.00 am which is a rush hour in the system. $P_s(t)$ in the considered node decreases during the perturbation until the end of the perturbation and still unstable two hours after the end of the perturbation. The instability period in this model is due to the train schedule which is not exactly like the train schedule during normal operation of the system. The simulation with the perturbation scenario shows that for the entire network, the passengers' delay is about 11 minutes per passenger. Compared to passengers' delay during normal operation of the system i.e. 7

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minutes, we can say that the impact of this perturbation on the global network is less important than its local impact since locally, the performance of the system, $P_s(t)$ decreases by half (cf. Figure 2).
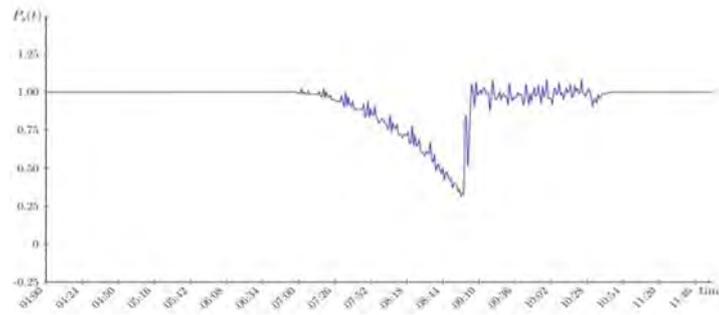

Figure 2. Curve of $P_s(t)$, at node *s* during the perturbation scenario.

4- MODELLING CRISIS MANAGEMENT PLANS

Before injecting crisis management plans in the model, one simulates the behaviour of the passengers. When the time spent by a passenger waiting for a train exceeds 30 minutes, the passenger will try to take another line with a probability of 80%, and thus change his path by avoiding the line or the arcs on which the perturbation occurs. This is possible only if the passenger is at a station where he can make a connection. In the next version of the model of the simulation, passenger behaviour that consists of leaving the system or changing destination will be taken into consideration.

Figure 3 shows the curve of $P_s(t)$ during the perturbation scenario. The blue curve represents the performance indicator without the simulation of passenger behaviour and the red curve is the simulation of the perturbation scenario with passenger behaviour. There is reduction of load in the node when we add the behaviour of passengers to the model. But the instability period of the system when we add passenger behaviour doesn't change, i.e. two hours after the end of the perturbation. The passengers' delay of the system decreases from 11 minutes to 10 minutes and 30 seconds.

This behaviour of passengers during perturbation can be modified by crisis management plan. Indeed, if crisis managers give enough and precise information to passengers about the perturbation, they could decide to change their path earlier.
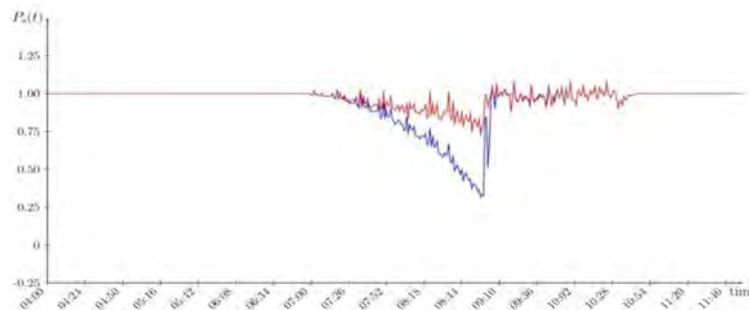

Figure 3. Curve of $P_s(t)$, at node *s* during the perturbation scenario. The red curve represents the simulation with passenger behaviour and the blue curve is without passenger behaviour.

The crisis management plan that is modelled consists in delivering targeted and relevant information to passengers and adopting harsh measures to deter travellers in such a way that they can change their path before reaching the failed arcs. At result, we assume that 15 minutes after the beginning of the perturbation, all passengers in the system are informed about the perturbation in such a way that passengers that have the affected arcs in their path change their path. As we can see in Figure 4, the local performance in the considered node increases considerably when we simulate the crisis management plan. The reduction of passengers' delay is also observed from 11 minutes to 10 minutes. The passengers' delay doesn't decrease enough compared to the delay obtained without any management plan nor passenger behaviour. There are different reasons for that:

- At 83% of nodes on the line on which the perturbation occurs, there is no possibility to make a connection with another line. So for the most of passengers who have one of these nodes as their origin or destination, they can't change their path.
- Fifteen minutes after the beginning of the perturbation, many trains, and thus many passengers, can be

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blocked between two stations (e.g. in tunnels). For these passengers, there is no possibility to move from their location until the end of the perturbation. Crisis management plans should be set up to prevent trains carrying passengers from leaving stations on the perturbed line earlier after the beginning of the perturbation. This implies a good ability of the system to detect and analyse the perturbation.

In order to considerably reduce the delay of passengers, other types of crisis management plans are necessary. For example, send more maintenance workers on the location (resourcefulness, redundancy) of the perturbation in order to help the system to recover quickly (rapidity) from this perturbation.
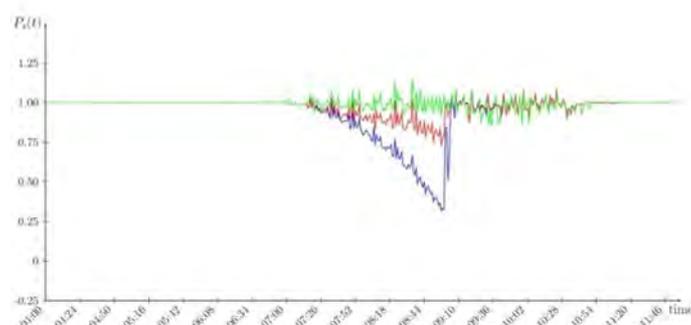

Figure 4. Curve of $P_s(t)$: The red curve represents the simulation with passenger behaviour; the blue curve is without passenger behaviour; the green curve is without passenger behaviour but with a crisis management plan.

5- CONCLUSION AND PERSPECTIVES

A simulation-based approach is presented in this work to quantify railway transportation system resilience indicators. The model aims to replicate normal operation of railway transportation system through passenger flow in the system. It is simulated on railway transportation system composed of 360 stations and 18 lines. The perturbation scenarios and crisis management plans are simulated to help the system to cope with these perturbation scenarios. The impact of perturbation scenario and the efficiency of crisis management plans on the system are assessed through the above mentioned indicators. The results show that efficient crisis management plans can considerably reduce the impact of perturbation scenarios on the system.

For the purpose of resilience quantification, more complex and realistic perturbation scenarios and other indicators like the impact of a perturbation on the system's environment should be considered. Further improvements of the proposed model include the introduction of more complex journey paths for the simulation of passengers' decision to take into account their perception of risk in time of crisis or potential danger.

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