A new Revenue Optimization Tool for High-Speed Railway
Finding the Right Equilibrium between Revenue Growth and Commercial Objectives

Mariane Riss*, Jean-Philippe Côté** and Gilles Savard***
*SNCF, Paris, France,
**ExPretio Technologies and ***École Polytechnique, Montréal, Canada

Abstract

In order to better tackle airline competition and to prepare for the upcoming deregulation of European rail transportation over the coming years, SNCF (the French national railway operator) is working in partnership with ExPretio Technologies to develop a new-generation Revenue Optimization tool. This tool, built on a "bilevel" mathematical optimization model, allows to take explicitly into account customer purchase behaviour and the offers of competitors. This new approach, initially developed at the Center for Research on Transportation (CRT) of the University of Montréal and École Polytechnique Montréal to fulfill the needs of airlines, is now being adapted to SNCF’s and its affiliates’ business context (fare structure, nature of the customer base, inventory management policies and practices, etc.).

In this talk, we present this new Revenue Optimization approach and contrast it with more classical methods currently applied in this field. We also underline the benefits brought by our model and discuss some results obtained through large-scale, live benchmarks. We conclude by listing some areas where we can improve the model as we go through the industrialisation and deployment of the tool.

The aim of this paper is to discuss the following points:
1) Why is it important to model customer behavior in railway Revenue Management?
2) What are really the commercial objectives of the transporters?
3) An integrated approach based on bilevel programming
4) Experiment with the train-operator THALYS

Introduction

This paper follows a first talk given at the Montreal WCRR 2006 conference.

In that first paper, we described the factors that characterize the commercial strategy of a national railway operator such and SNCF and, by illustrating why previous approaches have not proven satisfactory, we made the case for a new generation of revenue optimization tools. Since then, our new Revenue Optimization approach has been thoroughly tested and validated in a series of live benchmarks throughout the winter of 2007. These tests have demonstrated the financial potential of our approach and have allowed us to identify various areas in which we can improve our tool, in order to better meet the expectations of inventory managers and marketing experts.

This new tool, which is integrated in SNCF’s information technology and data-processing environment, consists of a combinatorial optimization model, a demand forecasting model, and a customer behaviour model. This innovative approach places customer purchase behaviour at the centre of the modelling process. Indeed, contrary to traditional RM approaches, we do not suppose that demand forecasts are independent and that customers are captive of one given type of product. In our model,
the customer has access to complete information about the transportation services being offered on
the market and makes purchase decision according to his own preferences and choice criteria.

The remainder of this paper is organized as follows. We first discuss the importance of the customer
behavior modeling process in our application context (high-speed railway transportation). We then
introduce the environment and the global objectives (commercial strategy, social mission of the
enterprise, preparedness for deregulation, etc.) that our tool will help attaining. This is followed by a
presentation of the modeling approach that globally integrates these two aspects (customer behavior
and the company’s objectives) into a single, coherent mathematical framework. Finally, we present
some empirical results that were gathered during a real-life testing phase of our tool.

1) Why is it important to model customer behavior in railway Revenue Management?

a. Classical approaches: optimization with captive customers

Classical Revenue Optimization (also called Revenue Management) approaches, many of which are
still widely used today in the airline and railway industries, were focused on Forecasting/Inventory
Management [2] and rely on rather strong assumptions:

- Demand forecasts are established independently for each fare product (or booking class) on
each itinerary,
- Demand for each class/itinerary combination is independent,
- First and Second Class of comfort demand are separated,
- Low-value products are necessarily bought before high-value ones.

These basic assumptions were historically justified in the airline industry by arguing that the presence
of fare fences (for instance, the obligation for the passenger to spend one Saturday night at the
destination before the return flight) kept different types of passengers to specific booking classes.
However, such fences are currently disappearing from airline and railway industries, following the fare-
simplification revolution initiated by low-cost carriers. Furthermore, the development of the Internet and
a privileged and easy-to-use distribution channel now provides the customer with a wealth of
information and purchase choices. Finally, fare products offered by operators are nowadays more
imaginative, flexible, and can often be bundled with other complementary services at the time of
purchase.

The classical approaches are therefore rendered obsolete by these new factors and justify the
development of new approaches that are more appropriate to the new commercial environment, in
particular in a railway context.

b. A new and innovative approach: optimization with accounting of customer behaviour

The rational behind our new approach is to put choice and behaviour modeling back at the center of
the optimization process. In order to achieve this goal and realistically represent the reaction of
customers to what is being offered on the market, we base ourselves on mathematical objects called
“choice models”.

Choice models have been studied in econometrics since the 1970’s and nowadays benefit from a rich
literature illustrating their properties. They have until recently been almost exclusively applied to
problems of a macro-economic nature characterized by relatively few variables, for instance,
predicting market share of a means of transportation in an urban agglomeration, or measuring the
impact of regulatory measures imposed on the telecommunications market. Their use as operational
tools for commercial planning, optimization and marketing is, however, novel.
Choice models are based around the notion of utility. Given a customer’s choice set, composed of two or more choice alternatives, the utility of a given alternative in the set is a numerical expression of preference for that alternative. Let $I$ be the set of alternatives composing a customer’s choice set. The utility of alternative $i \in I$, denoted $U_i$, is represented as

$$ U_i = V_i + \zeta, $$

where $V_i$ denotes the deterministic part of utility and $\zeta$ is a (continuous) random noise whose density function is denoted by $z$. Suppose that alternative $i$ is characterized by a number of attributes. In the context of passenger rail transportation, alternatives correspond to itinerary/fare combinations, while possible attributes of an alternative include price, departure or arrival time, travel duration, physical comfort level (first or second class carriage), refund possibility, etc. Let vector $x_i$ represent the attributes of alternative $i$. Even though several attributes may be considered, they do not contribute in the same proportion to an alternative’s total utility. In order to express the weight of each attribute, we use vector $\beta$. Thus, the deterministic part of utility takes the form $V_i = \beta x_i$, which means that the utility of alternative $i$ is expressed as

$$ U_i = \beta x_i + \zeta. $$

Building upon these concepts, we may now define a choice model as a probability function $P$ over set $I$ and parameterized by vectors $\beta$ and $x$ which assigns a choice probability $P_i(\beta, x)$ to each alternative $i \in I$ by supposing that customers seek to maximize utility when making a purchase. The distribution of choice probabilities depends of the distribution of random noise variable $\zeta$. For instance, if $\zeta$ is a constant, then the alternative with the largest utility is chosen with probability 1, while all other alternatives have a choice probability of 0. In the case where $\zeta$ follows a Gumbel probability distribution, that is $\zeta = e^{-e^{-\zeta}}$, one derives the well-know LOGIT choice model (note that the equation given above gives the “standardized” form of the Gumbel distribution, with “location” parameter set to 0 and “scale” parameter set to 1). The main advantage of the LOGIT model is that the choice probabilities it induces are expressed by a closed formula:

$$ P_i(\beta, x) = \frac{e^{\beta x_i}}{\sum_{j=1}^{I} e^{\beta x_j}}. $$

The attractiveness of this simple formula must however be counterweighed by the well-documented limitations of the basic LOGIT model (for which the reasons go beyond the scope of the current paper). Over the years, several workarounds have been proposed, which led to the development of more sophisticated, LOGIT-based models displaying properties more suitable for a practical application. While being more delicate to handle from a numerical point of view, the more elaborate members of the LOGIT family offer more realism to the modeler. Other families of choice models, for instance the PROBIT family, which is based on a normal (Gaussian) rather than Gumbel noise distribution, also has its pros and cons. The choice of a particular model therefore depends on the problem at hand and reflects a tradeoff between the available computational power (and time) and the level of realism deemed acceptable by the modeler.

Notwithstanding the exact type of choice model, such an approach offers major advantages over traditional, statistical-based Revenue Management methods. A choice model does away with the classical demand independence hypothesis. In fact, instead of forecasting demand at a low level of granularity (for each booking class on each train), one can forecast aggregate demand (say at market level for a weekday morning) and let the choice model distribute demand on choice alternatives, which
more truthfully reflect how modern customers having access to comprehensive online information make their purchase decisions. Indeed, all relevant alternatives are considered (“I’d like to take the express at 7:45, but the 7:30 and 8:00 trains still have some inexpensive seats available”) and travelers chose the one that maximizes their utility (“All things considered, I’m better off with the 7:30 train, it will take a little longer but I’ll still arrive on time and save on price”).

One important step when using a choice model is the calibration of parameter vector $\beta$ from historical booking data. More precisely, the calibration procedure seeks to estimate, based on statistical metrics, the utility function weight of choice attributes, reflecting what has been empirically observed in past data. We therefore seek to understand how customers have in the (recent) past behaved and what criteria have influenced their decision. Once this information is known, it is used to predict future customer behavior by applying vector $\beta$ to model upcoming choices.

The generation of the customer’s choice set is an important step of the overall process. Two important factors influence this set:

- The availability of the fare products (or alternative products from competition) which is related to the moment (or interval) the customer makes his choice (anticipation).
- The characteristics of the customer and the objective of the desired travel (leisure vs business, market). Commercial restrictions such as commercial cards can give access to specific products.

Two approaches are available to incorporate the choice set step into the process, according to the level of details of the discrete choices models. The first one consists of segmentation, a priori, of the customers into various and specific classes according to the above factors (e.g. frequent business travelers under 26 (having access to a specific commercial card)). This approach, which has been retained for the tests presented in the last section, allows for a specific discrete choice model for each segment class. The second approach requires less segment classes but more sophisticated choice models by using the notion of latent classes. These choice models incorporate more factors such as the notion of anticipation. SNCF is currently pursuing research on such discrete choices models [3].

Both approaches require for each segment of customers an estimate of the demand. The forecasting model estimates the number of bookings according to:

- Market
- Date – choice interval of departure (e.g. rush hour in the morning)
- Date of request
- Specificities of the segment

Finally, these three steps done (segmentation, choices set generation and forecasting), the discrete choice models gives a detailed forecast on:

- Train (date/hour)
- Date of request
- Fare product

This global approach allows for a recapture between products, trains or transporters and can give estimates on cross-elasticities.

2) What are really the commercial objectives of the transporters?

SNCF has been for a long time, a monopoly, and has a mission of public service. Its goal has not really been the turnover but rather to prove how its service is efficient and deserves the French
interest. An obvious indicator of such mission was and still is the filling of the trains. Today, competition challenges the rail industry in Europe and in particular SNCF.

High-speed railway service, called TGV (Train à grande vitesse), has become a staple of everyday life in France. With the completion in recent years of high-speed links between Paris and the Mediterranean basin, SNCF has entered in direct competition with airlines for time-sensitive passengers who previously traveled almost exclusively by plane. Even if the competition from the airlines was there for many years on some markets, the recent airline partnerships opening the Europe's skies and the availability of low-cost offers have increased the pressure of airlines. Paris-Amsterdam is another example where the competition will increase between airlines and rail with the completion of high-speed liaison between these two cities.

Europe is also getting ready for the progressive deregulation of passenger rail transportation that is scheduled to gradually take place in 2010. In this new commercial reality, traditional, state-owned railway operators such as SNCF will face new competition on their own networks. Already, France has seen its first ever “non-SNCF” cargo train circulating in June 2005.

In the airline industry, deregulation of air transport has led to significant change in the way airline industries managed their commercial operations. This new competitive environment has forced airline to better manage their capacity, which lead to the development of the yield management approach and the notion of revenue maximizing. In the last few years, SNCF has gradually evolved to deal with this upcoming new competitive environment. Even if revenues remain a major indicator of efficiency, the objective of the SNCF for the next years cannot be reduced to this sole indicator. Indeed, SNCF may have few objectives (and/or constraints) such has:

- Revenues
- Filling of trains
- Market share
- Accessibility and attractiveness (promotion)
- Long term fidelity

Given the commercial objectives of the SNCF and the competitive environment, the goal is now to compute the right equilibrium between the offer and the demand.

3) An integrated approach based on bilevel programming

In game theory, it is frequent to encounter situations where conflicting agents are taking actions according to a predefined sequence of play. For instance, in the Stackelberg version of duopolistic equilibrium [4], a leader firm incorporates within its decision process the reaction of the follower firm to its course of action. If we consider the leader as SNCF, the follower (in term of sequence of action) corresponds to the market, which reacts to the decision of the leader (in terms of inventory of seats and prices). If both agents are represented through a pair of arbitrary mathematical programs, one obtains the class of bilevel programs.

In our bilevel Revenue Optimization model, we modelize the market reaction to the travel offers (both from the carrier and competitors) by using discrete choice models. This approach therefore provides us with a fine-grain mathematical representation of the market’s reaction and an estimation of the level of correlation (interdependence) amongst the alternatives faced by customers. The model corresponding to the firm consists of maximizing its utility by controlling two levels of variables (availability of products and price) subjected to given constraints. As discussed previously, the identification of the utility function and/or constraints may vary according to the current commercial objective of the firm. Schematically, we can present the model as:
First level: Firm (SNCF)

Objective: maximizing the current utility function of revenue
subject to:

- Social constraints
- Commercial and networks constraints
- Availability of products
- Competition offers

taking explicity into account the reaction of the market:

Second level: Market

Objective: maximizing the current utility function of the market
subject to:

- Demand satisfaction

The bilevel programming model is a difficult combinatorial program (indeed NP-complete) that requires specialized algorithms to solve it. The resolution approach generally developed is based on a linearization of the complementarity constraints obtained on the optimality conditions of the second level model, leading to a large scale mixed-integer programs.

4) Experiment with the train-operator THALYS

We present in this section preliminary results obtained with the model on two different tests performed on the network of THALYS. Like other high speed operators, THALYS international (of which SNCF is the main shareholder), has seen its competitive position in the transport market evolve over the last years. In a market previously dominated by the airline and road transportation, THALYS with its high speed network, connecting four countries (Holland, France, Belgium and Germany), has significantly increased its market share. If the inter-modal competition (air and automobile) has increased over the time, THALYS has observed an augmentation of the intra-modal competition and try to improve the turnover. One lever of action of the revenue management team is capacity allocation: all THALYS trains are capacity allocated, i.e., specific product availability is dependant on allocation, decided at train level by the analyst. So, THALYS’s objectives, in particular in term of turnover, are currently managed by the analyst. 

The demand on the THALYS network is extremely variable: trains are full at peak hours and sparsely filled in off-peak periods. The behaviour and the profile of the customers vary according to different markets (e.g. Paris-Brussels vs Paris-Köln). Competition is present on various markets. On Paris-Amsterdam, one million passengers have traveled on THALYS in 2007, representing about 46 % of the estimated market share, while on Paris-Koln, more than 550,000 passengers traveled, representing 45 % of the market share. On these markets, THALYS is in competition with both alliances and low cost airlines: AF, KLM, German wings, Air Berlin, Vueling, etc. car remains the main competitor, particularly between Paris-Brussels.

Collaboration between ExPretio and SNCF led to the adaptation of this previously described approach to THALYS’s context. More precisely, we integrated the firm’s commercial strategies and its particular constraints (network structure, capacities, schedules, etc.) into the model. This formulation has been recently tested “live” on the Thalys network. 

The tests have been conducted over two two-week periods over the winter of 2007. Each test started three months before the first circulation date (thus in the fall of 2006 for the first departing trains) corresponding to the moment at which seats start being offered for individual booking on the Thalys network. Since there were on average sixty trains circulating every day (each train servicing up to a dozen legs), about one thousand trains were entirely controlled by the model in automated mode (without human intervention whatsoever).
The tests relied on Thalys’ 2006-2007 fare grid and current commercial strategies: fixed price, inventory structure in net nesting (grouping fare products in buckets) and mandatory booking. Trains are managed one by one, bucket by bucket. Thalys’ marketing experts were involved during the calibration phase of the model and provided helpful information in the form of market surveys. From the onset, the objective of the live test was to increase revenue. The optimization lever which was completely left under the control of the model was the dynamic allocation of seats to Thalys’ booking bucket. The company’s inventory managers were closely involved in the test process. Their monitoring of the model’s actions and posterior analyses provided very valuable insight into ways to improve their practice and the model.

The following figures present the results for the two test periods (within the red frames). The objective has been met beyond the expectations and the results turned out to be very instructive and revealing of the behaviour of customers on the Thalys network.

More precisely, we give for a major market:
- the occupancy
- the revenue
- the average price
- the average price per available seat.

The comparisons are made with the same 15-week periods in 2006 and 2007. The tests periods were altered by many factors. The position of the end of winter holiday affected the sales on the first period. In addition the Thalys network experienced disruptions due to storms. We can see a postponement of leisure demand from weeks 3 and 4 to weeks 5 and 6 in 2007. This is partially explained by the fact that Thalys offered a lot of discount prices during these two last weeks. That also explains the decrease in the average price: seats were sales with low tariffs.
Through some statistical indicating factors we can follow the two tests periods. For example Gini (cf. the following figure) or the Shift and Share factors confirm the impact of the model on the demand, more precisely on the structure of the sale’s shares. Econometric models give the evidence of the evolution of the relation between sales strategies and demands during the sample period.

![Gini indice](image)

Although the results of this model have been very positive from a financial point of view, the dynamics of the inventory controls set by the model in automated mode often departed from the type of controls usually imposed by human inventory managers. Indeed, controls from the model have been observed to be generally “tighter” than quotas implemented by analysts, which in the long run could have an impact on leisure demand for instance.

Work remains to be done in order to further constrain the model so that its results translate into the kind of actions that inventory controllers and marketing experts want to implement. For instance, one additional objective, besides revenue maximization, could be to optimally balance load across all trains scheduled on a given day on a same origin-destination pair. Although this may not translate into additional revenue for the firm, a better load balance will increase operational efficiency and also passenger comfort.

This model evolution will allow us to continue meeting revenue targets while also satisfying the expectations of inventory and marketing experts in terms of operational constraints, commercial strategies, load balancing, optimal capacity utilization, etc. Overall, the goal is to deploy a tool that can ensure an adequate level of profitability and revenue growth while maintaining a high level of efficiency and accessibility, in line with the social mission of a state operator such as SNCF. For such, many others features are currently into development: complete cartography of each train, automatic incorporation of major events, automatic integration of the competition, etc.

**Conclusion**

As we will show in this talk, based on empirical experience, a new Revenue Optimization approach taking into account explicit customer behaviour can help in seizing additional revenue in a high-speed railway commercial context. However, revenue is not the only variable in the equation. Indeed, we must strive to find the right equilibrium between revenue growth and other important objectives (efficiency, accessibility, quality of service, etc.) pertaining to national railway operators such as SNCF and its Thalys subsidiary. In simple words, our goal could be stated as "no revenue dilution, but not empty trains either". We firmly believe that the modelling framework we present in this talk, based on
the bilevel mathematical optimization paradigm, allows us to achieve this equilibrium. Building upon the results from live tests, we will continue over the coming months to improve the model as we go to the industrialisation phase and the deployment of this new and very promising Revenue Optimisation tool.

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References


