Agent-based simulation as a support for price-setting in passenger transport

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KEYWORDS

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ABSTRACT

Companies operating in passenger transport face the challenge that they cannot easily assess the effects of pricing decisions they take. Particularly, many incumbent European Railways are revisiting their traditional pricing structures based on static distance-based fares and develop new ways for pricing their services. Building on insights of behavioural pricing and Revenue Management, I investigate on alternative, more revenue-efficient pricing structures for a focal railway company given individual passenger price reaction behaviour and intramodal competition. First experiments with the model suggest that a limited quota for permanent special offers is counterproductive, while an increase in fuel price gets relatively quickly absorbed by the market.

MOTIVATION

Pricing is a public transport operator's key parameter for stimulating demand by – for instance – allowing lower fares in exchange for higher utilisation of capacity in off-peak periods. Within their long-standing history, European railways have developed a specific pattern for pricing their services: the standard railway tariff relying basically on the kilometre travelled. Liberalisation in the European railway sector was partly introduced to overcome "dissatisfaction with the price and quality of rail transport" (European Commission 1996: 3), hoping for similar effects as those observed in the airline and telecommunications branches. But up to the present, a large number of contemporary rail operators' pricing strategy remains quite far away from dynamic forms of pricing, even including newly-founded companies. On the other hand, many airlines are struggling with revenue management practices as competition leads them to a downward drive of their prices. Is there a more efficient way of pricing for railways beyond copying airlines and keeping the static tariff?

THEORETICAL BACKGROUND

Definitions

Belobaba (2009: 73) defines pricing in passenger transport as "the process of determining the fare levels, combined with various service amenities and restrictions […]". Tariffs in the railway sector are fares and conditions of carriage set by train operating companies. A tariff structure in this paper is seen as the conceptual framework for the collective fares of an operator. In the following, railway tariffing is examined within the framework of general pricing theory including revenue management approaches and the concept of path dependence.

Pricing: from production cost to revenue management

In management literature, explicit theoretical assumptions of how and when prices are set or changed are not always easily found. Primarily, problems of pricing are addressed in marketing science, where pricing is seen as the most prominent element of the marketing-mix.

While the price of a good was commonly perceived as the value of its production cost in the classic era of economic thought, neoclassical scholars introduced the concept of a market price fitting utility-based demand and cost-based supply. Before the equilibrium price is attained, a Walrasian auctioneer excludes any transaction. Otherwise, multiple equilibria differing from the theoretical optimum are possible (cf. Jaffé 1967; Bridel & Huck 2002).

Using insights from psychology, behavioural pricing theorists focus on understanding and explaining the complex individual processes triggered by price stimuli. Based on the theory of reference prices (Helson 1964; Monroe 1973), Kahneman & Tversky (1979) find evidence for irrational behaviour that stands in contrast to neoclassical assumptions on utility; and thus present an alternative utility concept with their Prospect Theory. Thaler (1985) further develops these insights to a theory on mental accounting. This way of accounting does not follow rational rules, but is deeply shaped by individual coding. As an example, see biased flat-rate and pay-per-use decisions observed by Lambrecht & Skiera (2006).

Revenue (or yield) management can certainly be seen as one of the most famous pricing practices in the last

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decades, as managing supply and demand through manipulation of product availability in time has spread to a variety of industries. Belobaba (2009) lists three "economic principles" (p. 76) for determining prices: cost-based, demand-based (i. e. pure price discrimination), and service-based (i. e. product differentiation) pricing. For Talluri & van Ryzin (2004), the innovation of revenue management consists in providing "technologically sophisticated, detailed, and intensely operational" (p. 4) methods of decision-making dedicated for increasing revenue.

Explaining rigidity: organisational path dependence

The concept of path dependence is a widely used approach in the social sciences. Building on the pioneering work of David (1985) and Arthur (1989), Sydow et al. (2009) define the phenomenon of path dependence for organisations "as rigidified, potentially inefficient action pattern built up by the unintended consequences of former decisions and positive feedback processes" (p. 696). Generally, a path-dependent process is characterised by a set of properties comprising contingency, a (limited) multiplicity of potential outcomes, self-reinforcing mechanisms, and lock-in. Sydow et al. (ibid) substantiate self-reinforcing mechanisms as coordination effects, complementarity effects, learning effects, and adaptive expectation effects. Being locked-in means for agents in the affected area that their scope of action is limited in a way that their agency can just reproduce the status quo. This stadium can be considered as at least potentially inefficient if it comes to a change in the environmental situation.

RESEARCH OBJECTIVES

Inertia and potential inefficiency of pricing is a topic that has so far been avoided by many scholars. Dutta et al. (2003) describe pricing as a "strategic capability" rarely addressed by researchers "because [they] assume that the processes by which prices are set or changed are relatively costless or simple […]" (p. 616). Miller & Page (2007) recommend research effort on the question how markets generally equilibrate: "Is there a coherent, plausible model that can help us understand the mechanism by which prices form in decentrali[s]ed markets?" (p. 243). The real-world process of price formation is obviously not the Walrasian one, nor can middle-range theories on individual price reaction fully explain it. Particularly, other than the concept of path dependence, conventional pricing theory lacks to explain the emergence of a persistent suboptimal pricing pattern. In contrast to the airline industry, revenue management problems have rarely been studied on passenger train operating companies (cf. Sato & Sawaki 2012). From their survey on railway revenue management literature, Armstrong & Meissner (2010) recommend to "bring passenger rail pricing to the same level that is [] seen in more mature areas of revenue management" (p. 19). This work is aimed at answering the question what price parameters would constitute a – ceteris paribus – superior tariff structure to the predominant distance-based, static portfolio for a contemporary passenger train operator. As a starting point for research on alternative options of pricing, the path formation process of the railway tariffing standard in Europe has been reconstructed using the path constitution analysis method outlined by Sydow et al. (2012). It can be shown that the described typical railway tariff remained a prevalent pricing pattern of European railways for decades despite of deteriorating economic situation of European railways since the late 1960s. The following research question results:

What railway tariff structure(s) produce(s) a more efficient outcome in terms of revenue than the static distance-based tariff?

METHOD

In order to explore on a more revenue-efficient set of price parameters for railways, pricing policy of suppliers under competition and behavioural individual reactions to the price stimulus on the demand side are observed with the help of an agent-based simulation model (cf. Gilbert & Troitzsch 2010; Gilbert 2008). Within the framework of the model, parameters can be manipulated under ceteris paribus conditions. Through running the model repeatedly, outcomes of these manipulations can be analysed statistically.

Computational modelling in general and agent-based objects in specific have gained broader acceptance among social scientists in recent years (Miller & Page 2007; Harrison et al. 2007; Davis et al. 2007). Simulation models have been introduced in operations research for capturing the dynamics of pricing measures and demand reactions after a number of time periods (cf. Cleophas 2012; Bitran & Caldentey 2003). Agent-based models are specifically suitable for revenue simulations because they "support the creation [of] autonomous agents that flexibly learn about and interact with their environment and with each other" (Cleophas 2012: 241). This allows for exploring revenue effects of price measures introduced at different points of time.

A revenue-inefficient or suboptimal tariff structure in this context can be perceived as a less elevated plateau or summit on a NK performance landscape (Porter & Siggelkow 2008; Rivkin & Siggelkow 2002; Siggelkow 2001).

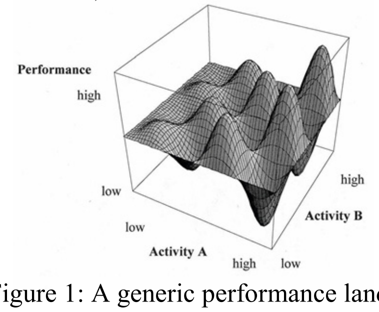

Figure 1: A generic performance landscape
(Source: Porter & Siggelkow 2008: 39)

In the realm of tariff strategy, different dimensions (e. g., fixed vs. flexible pricing and non-restricted vs. perfectly restricted) can be tested on local optima. Described graphically, some combinations of elements of a tariff structure may form a "revenue summit.

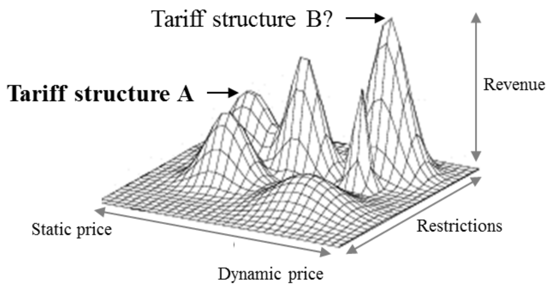

Figure 2: Local revenue optima within two dimensions (Source: own figure based on Verel 2012)

All possible measures of pricing are supposed to trigger a certain market reaction as proposed by Prospect Theory (Kahneman/Tversky 1979). In order to enable individuals to "calculate" their utility for a given fare, the theory is operationalised according to Nitzsch 1998 (p. 630):

- let *U(p)* the utility in function of the price
- let *la* the individual loss aversion factor
- let c=2 $\ln\left(\frac{1}{r}-1\right)$
- let *r* a sensitivity parameter 0.5<r<1. The higher it is, the faster sensitivity decreases
- let *norm* a parameter that allows to align the utility values to U(reference price ./. norm) = 1 (however, *norm* can be set to any other value except 0, too).

For p <= reference price

$$(1)\quad U(p) = \frac{1-e^{-c\left(\frac{reference\ price-p}{norm}\right)}}{1-e^{-c}}$$

For p > reference price:

$$(2)\quad U(p) = -la\left(\frac{1-e^{-c\left(\frac{p-reference\ price}{norm}\right)}}{1-e^{-c}}\right)$$

The choice function involves a reference price that further develops with any (memorised) transaction made as well as some product-specific features. For calibrating the model, the set-up of the simulator is closely aligned with the revenue management branch of a train operator. Market research data for precisely shaping customer preferences as well as booking data for the line under investigation are provided by this source.

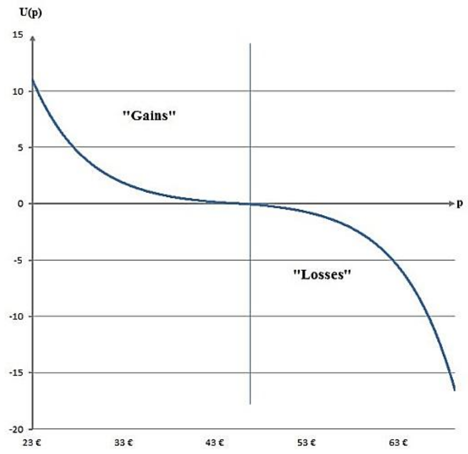

Figure 3: Utility as a function of the reference price (Source: own figure)

THE MODEL

The simulation environment is used as a setting for artificial experiments. It has been set up on the Netlogo platform, which is a fully programmable open source environment developed at Northwestern University. The model is programmed in a building block principle (Harrison et al. 2007), thus, by starting with a simple market transaction model which is subsequently elaborated with more complexity (e. g., rules of supplier behaviour in case of intramodal competition; mutual monitoring of passengers; fuzzy memory of passengers).

In its formal structure, the model contains a limited number of agents on the supply side (train, bus, air operators) and a multitude of individual agents on the demand side. A part of this population is provided with an individual car. Therefore, car transit acts as a passive transport operator. Every period of time (tick), a mobility demand is injected to a random part of the demand side. Then, individuals seek to fulfil their demand by searching a transport offer that rewards them with maximal utility calculated out of the operationalised price reaction function derived from Prospect Theory. For computational performance reasons, it is not possible to model the entire network of an incumbent train operator. Therefore, two highly frequented long-distance lines have been selected for being modelled.

In more detail, the supply side can be set to one, two, or three public transport operators with an own tariff structure involving a base fare, rebates and optional application of quantity-based revenue management. The agentset of passengers receives a monthly mobility budget and, besides individual features like age or links with others, is grouped into six sociological fractions representing their propensity to use public transport. The population of passengers is 5'000 individuals who are randomly interlinked to each other; half of them own a car. A part of the population is additionally equipped with a railcard. All passengers have a randomly set loss aversion factor between 1 and 2.

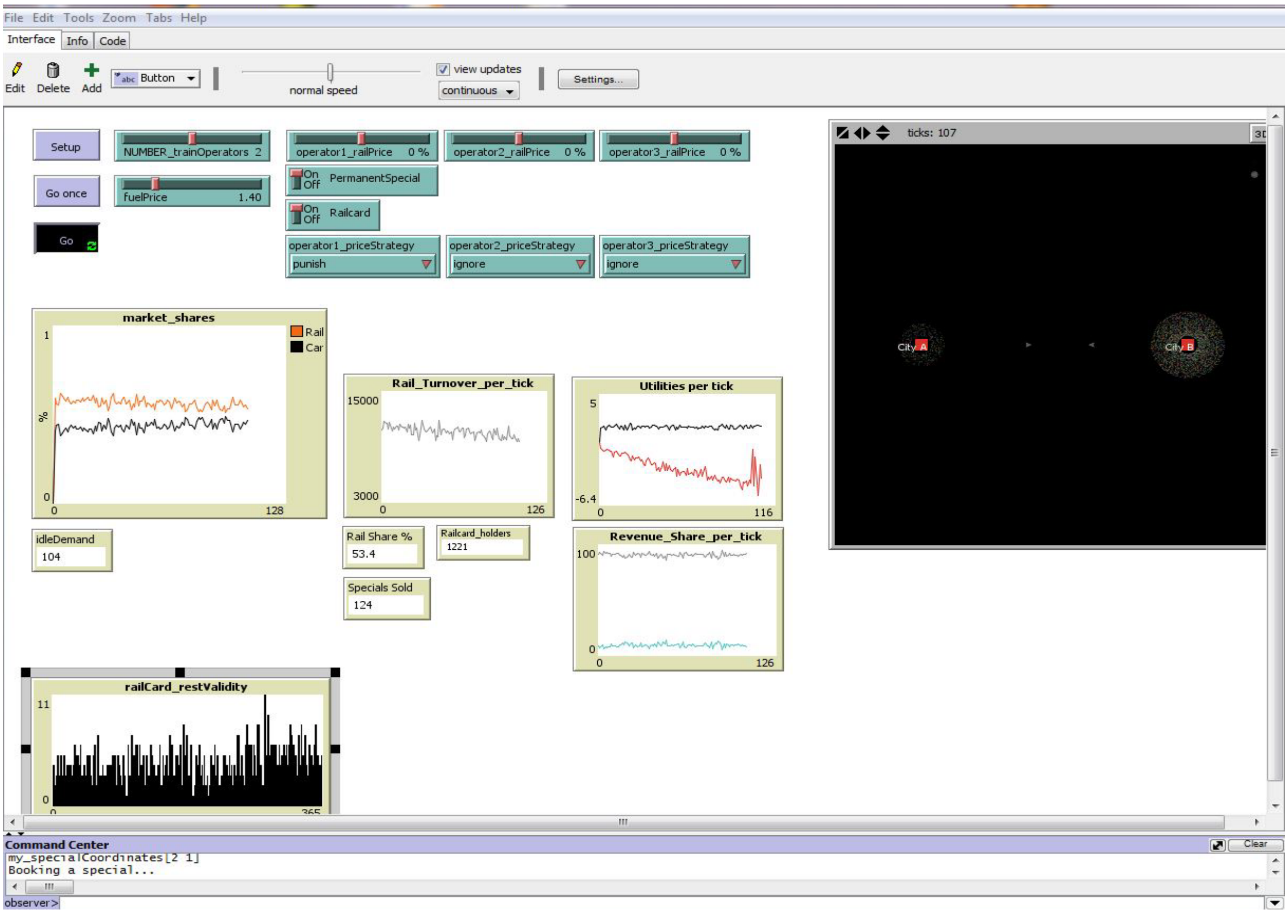

Figure 4: Screenshot of the Netlogo model for one origin-destination

After an initial learning phase, transport operators who use revenue management approaches create special offers and allocate a seat quota at different price levels. Passengers are always offered the cheapest fare fitting their demand. From their transactions, passengers memorise the price they have paid until they forget. There are several possible experiments within the current version of the model:

- Does the sheer application of Revenue management increase overall revenue, regardless what quota is allocated for the specials?
- Can permanent specials be a replacement for a railcard in case the latter is set off from the market?
- What is the long-term effect of a fuel price change?
- What is a more revenue-efficient quota of permanent special prices than a given one?
- Using the Behavior Search extension of Netlogo, what setting parameters is needed for obtaining a certain revenue target?
- Is there an optimal range of occupancy?

Relating to Prospect Theory, fuzziness of price memory can be tested against a “perfect” memory including a number of *n* last transactions. What is more, revenue effects related to marginal change of the loss aversion factor can easily be assessed. Later extensions of the model will involve competitive pricing between operators and a more active search for lower prices made by a part of the passengers.

PRELIMINARY RESULTS OF FIRST EXPERIMENTS

The base case scenario of the experiments made so far is as follows: agents could choose between individual car transport and a half-hourly frequency of trains operated by operator 1 as well as an hourly service of operator 2. Operator 2 doesn’t accept any railcards. Operator 1 grants a 50% discount for railcard holders. Revenue generated by selling railcards is neutral. The operators ignore each other’s pricing. Every tick, 500 agents receive a random mobility demand. For representing the features of the railway line, a time advantage of 20% in favour for rail was implemented; according to their sociological group, individuals accord a fix utility bonus to car transport.

The model in its basic features was run 50 times for 200 ticks each, which corresponds to a time of approximately six months. Within this framework, experiments for investigating on the revenue effects of the following scenarios have been conducted:

Scenario	Description
0	Base case (see description above)
1 “high specials quota”	After an initial learning phase of 100 ticks, operator 1 creates special prices for the 20% most under-utilised trains. There was a quota for a best-buy and a more expensive special. Operator 2 continues to use a fixed base fare only.
2 “low specials quota”	In this second experiment, the setting of experiment 1 was unchanged, except that the quota for permanent specials was reduced by 50%.
3 “Fuel price 10% up”	In this simple third experiment, the manipulation of the base case scenario consisted in computing a one-time 10% increase of the fuel price at tick 100.
4 “Railcard removal”	In the fourth experiment, the manipulation consisted in deactivating the railcard applicability after 100 ticks, with no regard to the rest validity of the cards. At the same time, operator 1’s base fare is reduced by 25%.

Table 1: First experiments with the model

Congruently to the base case, all manipulated models have been run 50 times for 200 ticks each. In all scenarios, the simulation is stopped after 200 ticks, thus, creating a total revenue out of 200 ticks.

Statistical results

After having conducted the experiments, data was collected and analysed by means of descriptive statistics. The following table shows revenue generated after 200 ticks for each operator as well as the total revenue generated by both rail operators across the base case (0) and scenarios 1 to 4.

		N	Mean	Std. Deviation
Operator1_Revenue	0	50	1.810.477	110.562
	1	50	1.779.026	87.668
	2	50	1.763.170	90.738
	3	50	1.856.922	102.566
	4	50	1.731.440	68.904
Operator2_Revenue	0	50	179.757	60.133
	1	50	181.546	53.172
	2	50	188.621	55.268
	3	50	183.951	56.536
	4	50	179.845	42.685
Total_Revenue	0	50	1.990.233	63.872
	1	50	1.960.572	46.213
	2	50	1.951.791	46.200
	3	50	2.040.873	80.810
	4	50	1.911.285	47.431

Table 2: Descriptives of experiments

The number of passenger agents getting a mobility demand was set arbitrarily due to performance constraints of the computer hardware. Hence, a robustness check for the base case was performed to elicit if the model produces similar results with 250 and 1,000 instead of 500 passenger agents. The model behaviour was the same across those numbers. Due to the still limited number of simulation runs, significance tests have not been performed.

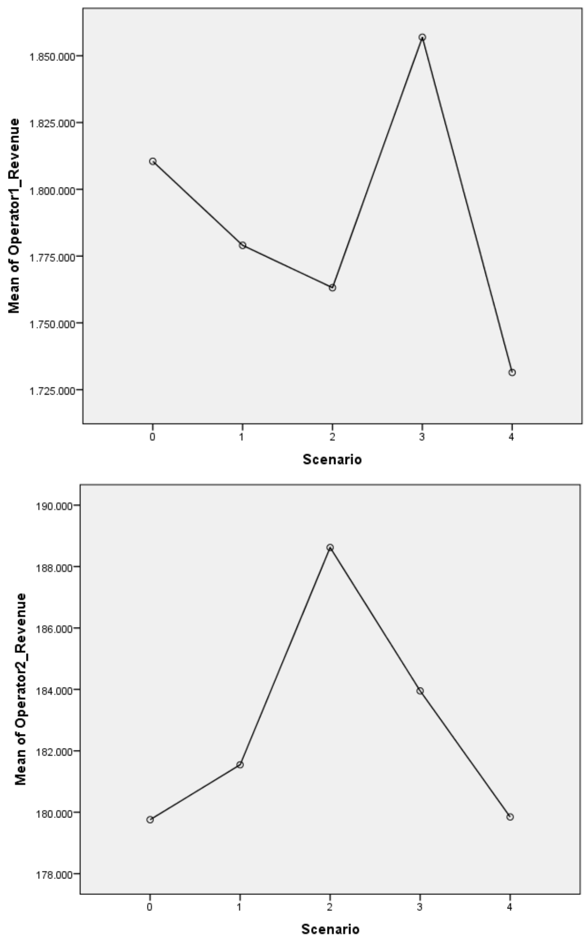

Figure 5: Effects of manipulations on each operator’s revenue

Interpretation

As suggested by Prospect Theory, individuals react sharply to prices higher than their individual reference price. For that reason, the positive utility effects of a special offer are easily foiled if no similar offer is found by the individual at a later occasion. The simulation model at its present state involves a strong dissatisfaction with a cheaper base fare of one of the operators because individuals aggregate a general “operatorless” rail reference price for themselves. It is interesting that a lower quota for special offers seems to reinforce that tendency, leading to a weaker revenue base for the operator who offers those specials and producing higher revenue for its competitor. However, further experiments need to be performed to find out if there is a coherent relation between the specials quota and the revenue generated by an operator who doesn't apply any specials.

In this context, functions of price competition strategies different from autonomous pricing (such as a price follower strategy) are currently being implemented in the model. A follower strategy may produce a significantly higher level of revenue for all suppliers.

Even though a higher fuel price causes frustration of the agents at first sight, it gets accepted on a longer run as the new reference price gets more and more memorised by the agents.

A removal of operator 1's railcard has literally no effect to operator 2, but seems to be unfavourable for operator 1. In this area, decision rules and search behaviour for passengers with railcards have to be refined to calibrate the impact of this rather eminent change in the tariff structure.

CONCLUSION & CONTRIBUTIONS

An agent-based simulation model can be used as a tool for assessing possible impacts of one or more pricing measures. Within the limitations of the model, a first indication on the effects of single price measures or consequences of the adoption of a radically new pricing strategy can be given. The processual character of the simulation is likely to reveal possible negative long-term effects of pricing measures that seem to be successful on a short run. The model continues to be calibrated and refined with more empirical data and more individual behaviour in choosing means of transport. Netlogo's Behavior Search extension permits to search for parameters needed to obtain a defined revenue target.

Bridging individual behaviour and aggregated market outcome through agent-based modelling contributes to marketing research as well as Revenue Management. The behavioural pricing aspect is susceptible for enriching operations research in Revenue Management, as recent research is more focused on individual strategic buying decisions of customers. For marketing, a ceteris-paribus analysis of changes in a tariff structure allows learning about large-scale effects of individual price reaction. Behavioural pricing inspired by Prospect Theory can be enriched through a very detailed parameterisation of the individual price-reaction-function.

On a general level, the potential of inertia (or an eventual lock-in), and inefficiency in the field of price-setting may form an impetus to re-think the way how prices are set and changed. This may provide insights for managers of transport operating companies, but also for policy-makers, e. g., in the European Commission, and management research in other industries.

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