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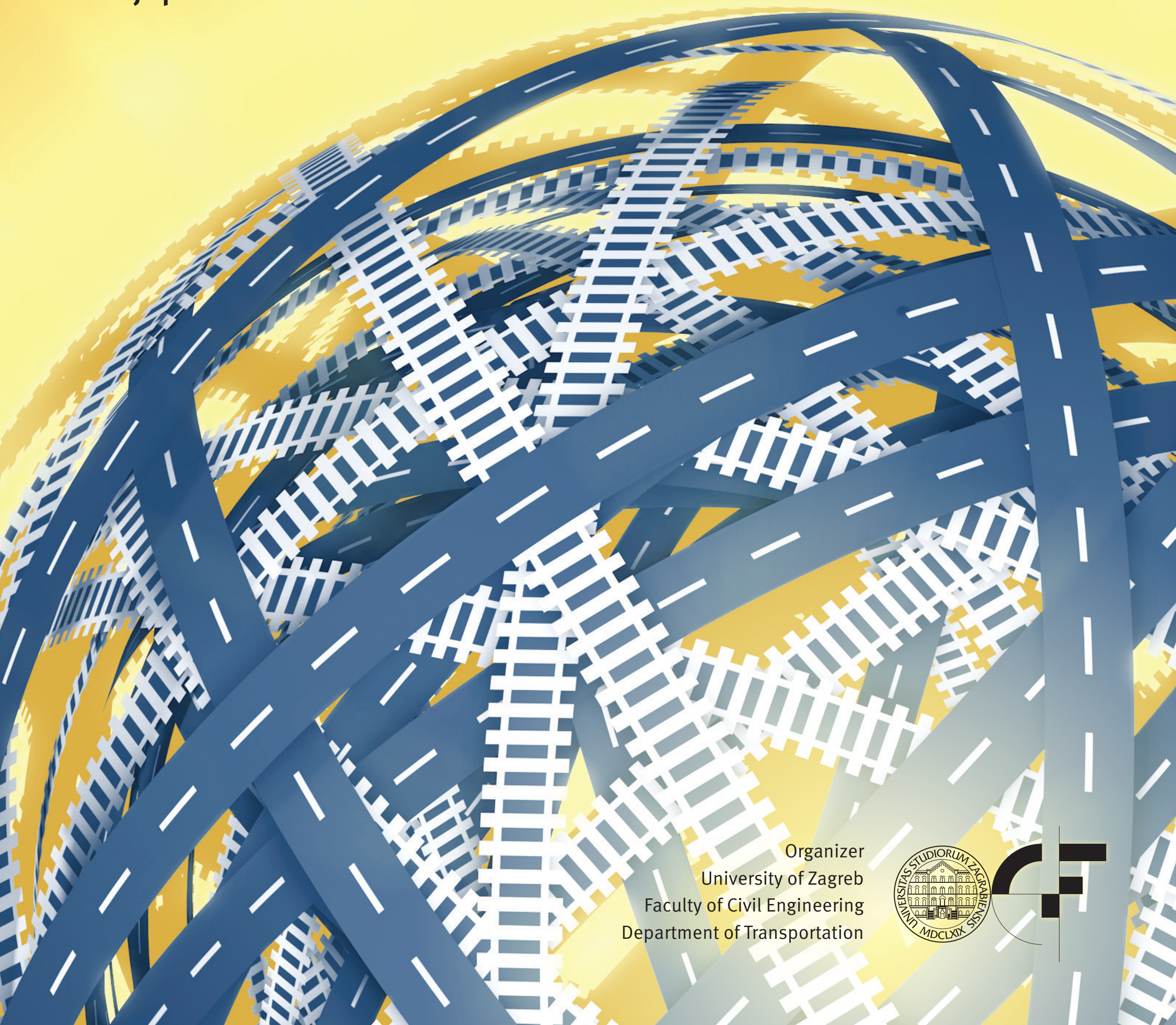
Road and Rail Infrastructure IV

Stjepan Lakušić – EDITOR



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HYBRID ALGORITHM FOR TICKET RESERVATION PROCESS IN PASSENGER RAIL TRANSPORT

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Abstract

Managing tickets reservation process in passenger rail transport is complex task. For solving this kind of task, we develop a hybrid algorithm based on Artificial Neural Network and Payoff table as a decision support tool. The aim of the proposed algorithm is to suggest real time decisions about seat inventory allocations taking into account information from the past. The paper considers the revenue management application in passenger rail transport with variable capacity of sleeping cars. Uncertainty of available capacity is embedded in developed algorithm by Payoff table, while Artificial Neural Network is used as a tool for making real time decisions. We consider nested reservation system, and the algorithm is tested on hypothetical data.

Keywords: Revenue management, Rail transport with variable capacity, Artificial Neural Network, Payoff table

1 Introduction

The main objective of Revenue Management (RM) concept is selling the right product/service to the right customer at the right time for the right price. This concept can be applied in models with following characteristics: a fixed amount of resources available for selling; the sold resources are perishable (time limitation of selling the resources, after which they don't have value); different customers are willing to pay a different price for the same product/service. RM is widely used in the transport industry, primarily in airline sector. In railway practice, Amtrak, intercity passenger rail company in United States, is a pioneer in the application of RM. This company introduced RM almost 25 years ago. Many other railway companies also apply RM concept, such se: SNCF (Société Nationale des Chemins de fer Français) in France; GNER (Great North Eastern Railway) in Britain; DB (Deutsche Bahn) in Germany; VR Group in Finland.

The hybrid algorithm for ticket reservation process management in passenger rail transport (sleeping cars) is developed in this paper. We consider nested reservation system with variable capacity. Railway operators in transition countries, including Western Balkans, that does not know in advance the available rail capacity, since very often rail cars are not ready for use due to repairs. The uncertainty of rail car preparedness in this paper is treated by Payoff table. The main contribution of the paper is developed decision support tool which is designed for making real time decisions concerning a new passenger's request, i.e. whether to accept or refuse it.

2 Hybrid algorithm description

2.1 Important assumptions

In this Subsection we provide basic assumptions relevant for our algorithm:

- The reservation of the highest tariff class berths is always possible if there are available berths on the train.
- Requests for lower tariff classes will be accepted only if rail operator expects lower demand for higher classes.
- Capacity is treated as a variable with several possible discrete values. This is an important part of the model due to the fact that the rail operators often do not know in advance a number of available sleeping cars or railcars. The probability of engaging new sleeping cars and penalties for a wrong estimation are involved in the model.

Decisions whether to accept a new request or not in real time are made by hybrid algorithm based on Artificial Neural Network (ANN) and Payoff table. First, we use a simulation for data base of realized sleeping car reservation process from the past. This data base contains information of time when the request is received and the type of requested tariff class. Having in mind the total number of requests per tariffs, we can offline apply linear integer programming in order to obtain an optimal revenue for one train from point A to point B. This means that one optimal solution, which indicates the way of managing reservation process in order to maximize revenue, is assigned to every realization of train trip. These data are then used for the ANN training. ANN is designed to give an answer whether to accept a new passenger's request or not in real time, with available capacity at the moment. Since there is uncertainty about available sleeping cars, we embedded probability of new rail car engagement through Payoff table. If ANN suggests rejecting a new request in the case of initial capacity (C_k), the algorithm consults Payoff table about capacity expanding. If decision maker expects capacity increasing, then the final decision is to accept new request and capacity value is changed from initial to new value. Otherwise, the request has to be rejected and reservation process terminates (Figure 1).

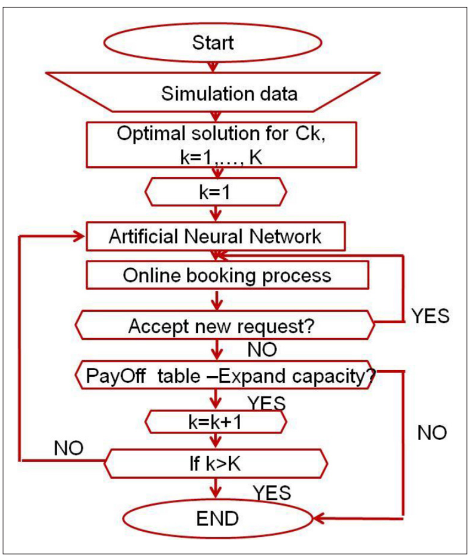

Figure 1 Hybrid algorithm

2.2 Simulation data

Table 1 contains cumulative numbers of the received requests for i-th tariff class in p-th realization of the reservation process obtained by simulation, and appropriate decision on accepting requests.

Table 1 Vectors of input and output values for p-th realization of reservation process

Time until closure reservation process	Cumulative numbers of received requests per classes				Decision for Class 1	Decision for Class 2	Decision for Class n
	Class 1	Class 2	…	Class n			
$t_p(1)$	$D_1^p(t_p(1))$	$D_2^p(t_p(1))$		$D_n^p(t_p(1))$	Accept	Accept	Reject
$t_p(2)$	$D_1^p(t_p(2))$	$D_2^p(t_p(2))$		$D_n^p(t_p(2))$	Accept	Reject	Reject
$t_p(3)$	$D_1^p(t_p(3))$	$D_2^p(t_p(3))$		$D_n^p(t_p(3))$	Accept	Reject	Reject
…	…	…		…	…	…	…
$t_p(Mp)$	$D_1^p(t_p(Mp))$	$D_2^p(t_p(Mp))$		$D_n^p(t_p(Mp))$	Accept	Reject	Reject

2.3 Model for obtaining optimal solution

Let us assume that it is possible to predict time of seat reservation request, as well as preferred tariff class. This idea can be valuable only for already realized rail trips. The problem of determining the maximal revenue in the case of sleeping cars with several tariff classes on non-stop leg can be optimally solved by linear integer programming:

$$(\max)F = \sum_{i=1}^{n} R_i x_i \tag{1}$$

Subject to:

$$C = \sum_{k=1}^{K} C_k \tag{2}$$

$$\sum_{i=1}^{n} x_i \leq C \tag{3}$$

$$x_i \leq D_i^p \quad i = 1,2,\dots,n \tag{4}$$

$$x_i \geq 0, \quad i = 1,2,\dots,n \tag{5}$$

$$x_i \text{ – integer variable} \tag{6}$$

$$R_{i:} > R_{i+1} \; i = 1,2,\dots,n-1 \tag{7}$$

Where:
p – realization of the reservation process (trip)
D_i^p – total number of received requests for i-th tariff class at the moment reservation process is closed ($D_i^p = D_i^p\,(t_z)$)
R_i – i-th tariff value
x_i – number of accepted requests (sold berths) for i-th tariff class at the moment reservation process is closed
C_k – capacity of k-th rail car
C – total available capacity.

Each summand in the objective function F (Eq. 1) represents revenue from berth sale in i-th tariff class. Total revenue for particular trip p can be obtained by summing revenue per all tariff classes. The available capacity is a sum of the engaged railcars capacities (Eq. 2). The number of the sold berths maximum can be equal to the capacity of the train (Eq. 3). The number of the sold berths in i-th tariff class cannot be larger than the number of requests (Eq. 4) for this particular tariff class at the end of the reservation process. The variables x_i are nonnegative and integer. Solving linear integer programming for each realized transport can ensure the determination of the maximal revenue and adequate number of berths per tariff class. In practice there are two possibilities: the number of requests is smaller or equal to the available capacity and the number of requests is larger than available capacity. In our paper we focus on more complicated, i.e. the second case (Pavković, 2000):

$$\sum_{i=1}^{n} D_i^p > C \tag{8}$$

In this case some passengers will not be able to buy tickets because the number of the received requests is larger than the available sleeping cars capacity. The optimal number of the tickets sold per each tariff for one trip, p, can be calculated in the following way (Pavković, 2000):

$$x_i = \max\left\{\min\left\{D_i^p, C - \sum_{k=1}^{i-1} D_k^p\right\}, 0\right\} \quad i = 1,2,\ldots,n \tag{9}$$

According to Eq. (9) it is possible to determine critical class, i_p*.

$$x_1 = D_1^p,\ x_{i^*_{p-1}} = C - \sum_{k=1}^{i_p^*-1} D_k^p,\ x_{i^*_{p+1}} = 0 \ldots\ldots x_n = 0 \tag{10}$$

For each already completed trip, the maximal revenue can be obtained by accepting all requests for berths up to i_p*-1 th (1,2,..., i_p*-1) tariff class, and some requests for critical class i_p*, while requests for other lower tariff classes (i_p*+1, i_p*+2, ..., n) must be rejected. Critical time, tp*, which starts with rejection of new requests (for tariff class i_p*), can be easily determined using database for trips already completed.

2.4 Real time decisions – Artificial Neural Network

Each realization of a rail trip has set of input and output values as shown in Table 1. In total, there are P tables (P trip realizations). These sets of input values (obtained by simulation process) and optimal output value (obtained offline by linear integer programming) are further used as training database for the ANN. ANN is used as a tool for decision making in relation to a new request in real time. ANN is technique that relies on a simplified brain model which basically learns from experience. The processing tasks are distributed over numerous neurons (nodes, units or processing elements). Even though individual nodes are capable of simple data processing, the main power of a neural network is the result of connectivity and collective behavior among the nodes (Teodorović and Šelmić, 2012). The inputs to the ANN consist of 6 relevant information e.g. input nodes:

- type of tariff class (first, second or third),
- discrete time interval when request is received (starts from 60 days before journey to one day before journey with increment of 10),
- number of requests per first tariff class (from the past),
- number of requests per second tariff class (from the past),

• number of requests per third tariff class (from the past),
• available capacity (from 6 to 12 sleeping cars, with increment of 2).

For certain inputs related to reservation process, ANN classify new request as accepted or rejected. The input layer has 6 nodes, and output has one nodes. The first layer is input layer, where the data are presented to the neural network. The values of the input variables are numerical values. The intermediate layer is the hidden layer. The third layer is the output layer, representing the network response to the corresponding input. The neural network can then be trained through a training algorithm. Currently, there are a number of training algorithms available for artificial neural network models, and the back-propagation rule, which is one of the most widely used training algorithms, is adopted in this paper.

2.5 Payoff table for variable capacity problem

The objective of the decision making process is to determine which decision should be chosen based on the payoff table. Payoff table (or Regret table) generates the payoffs for all combinations of decision alternatives and state of natures. Payoffs can be expressed in terms of profit, cost, time, distance or any other measure. The main goal is the reduction of regretting, so the optimal alternative is the one with the minimum regret.
In a payoff table the conditional opportunity loss (COL) and the expected opportunity loss (EOL) for all alternatives are presented. Expected opportunity loss or expected value of regrets represents the amount by which maximum possible profit will be reduced under various possible strategies. EOL is calculated by multiplying the COL's by associated probabilities and then adding the values. The optimal alternative is the one with the lowest EOL.
In the proposed model, there are two alternatives: a_1 – to increase train capacity, and a_2 – not to increase train capacity. New sleeping cars can be ready (with probability z) or not (with probability q (q=1-z)) for train departure. We made an assumption that increasing train capacity implies two new wagons more in the composition.
If we choose alternative a_1 (to increase train capacity) there are two outcomes: for the outcome 1 (the new sleeping cars are ready for train departure) there is no regret (COL=0); for the outcome 2 (the new sleeping cars are not ready for train departure) there is certain regret (COL1). For obtaining COL1, we assume that the passengers are entitled to refund for a cancelled train trip. If we choose alternative a_2 (not to increase train capacity) there are two outcomes (Table 2): for the outcome 1 (the new sleeping cars are ready for train departure) there is certain regret (COL2); for the outcome 2 (the new sleeping cars are not ready for train departure) there is no regret (COL=0). COL2 presents the company regrets for non realized profit (lost profit). In the considered example, optimal strategy should be defined as follow a_{opt} = min(EOL1, EOL2).

Table 2 Payoff table

	COL		**EOL**	
	a_1	**a_2**	**a_1**	**a_2**
Outcome 1 with z probability	0	COL2	0	z*COL2
Outcome 2 with q probability	COL1	0	q*COL1	0
Sum:			EOL1=0+q*COL1	EOL2=z*COL2+0

3 Results and discussion

The proposed model is tested on the hypothetical data. Demands for berths reservation are described by normal distribution, while times of reception of the requests are simulated by uniform distribution.

In this paper we assumed that passenger has three possibilities (three different tariff classes) for traveling by sleeping cars: Tourist ticket (passenger buys one regular rail ticket and one berth), Double (one regular rail ticket and two berths) or Single (one regular rail ticket and three berths). Obviously, Tourist ticket represents the cheapest tariff class, while Single is the most expensive one, i.e. the first class. The basic characteristics embedded in the model are:

- All berths are available for all tariff classes, and hence a number of sold tickets in each tariff class are known only after the reservation process being over.
- Demand for seats in all tariff classes is usually a random process.
- Demand is always larger than available capacity.
- In the reservation process, a number of available sleeping cars is not known in advance.
- The first-class tickets are always sold, i.e. all the requests for the first tariff class will be realized.

To estimate the ANN model, there are a number of software packages ready to perform the back-propagation algorithm, and MATLAB was chosen for this study. For the neural network used in this paper, three types of patterns have been taken into consideration (for the neural network training, validation and testing).
We have simulated data for 100 realizations. In total it is 8400 input and output data for ANN. For each realization we form table with 84 rows. During the training phase, the ANN has optimally classified a new passenger request as accepted or rejected in 99% of cases. When the test data were processed, an accurate matching was also 99% in all cases. The regression in the case of training, test, validation and all data is shown in Figure 2 where the x-axis shows the target values, while the y-axis shows the output values.

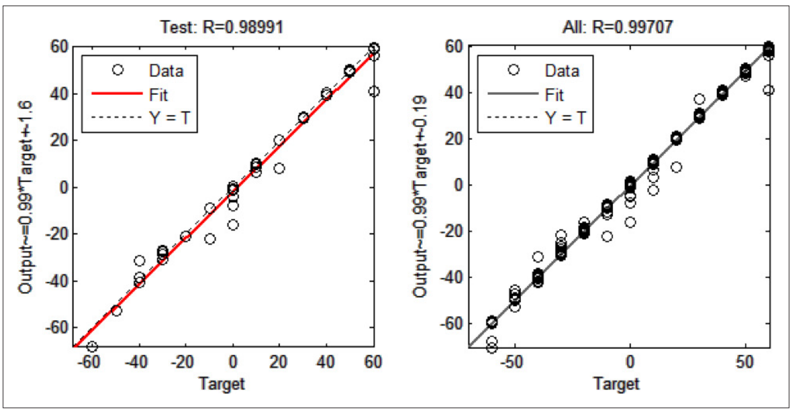

Figure 2 The matching of the output data to the target results (relation between the output data and the target results)

During reservation process rail operator could face with lack of available train capacity. Then it is necessary to make the decision about new sleeping car’s engagement. To make appropriate decision conditional values – COL should be multiplied by certain probabilities, and then obtained expected values should be summarized and compared. By comparison of these two values, the optimal alternative is defined.

4 Conclusion

This paper presents the application of Revenue Management concept for capacity allocation in railway industry. The proposed model is a decision support model developed for making real time decisions about accepting or rejecting new passenger request in rail transport. It is applicable for the issues with variable capacity. The proposed model, based on Artificial Neural Network and Payoff table, takes into account variable capacity of trains, and the uncertainty of rail car preparedness. The algorithm is tested on hypothetical data. The obtained results show great applicability of the model. Future research will consider rail network with multi-leg itinerary.

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