Booking limits and bid price based revenue management policies in rail freight transportation

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In this paper, the possibility and potential benefits of implementing discriminatory policies in rail freight transportation are analyzed, with the aim of revenue maximization. A regular, cyclic, single train service with fixed composition and capacity is studied. The problem is decomposed into discrete time periods. Transportation requests arise randomly over time, and the decision of either accept or reject a certain request has to be made. The problem is formulated via dynamic programming, and the deterministic approximations of the problem are used in order to formulate booking limits and bid price policies. Results obtained are compared with those of standard first come – first served policy, which is implemented by the Serbian railways. Although not acceptable in all contexts, the proposed aggressive policies demonstrated promising benefits.

Keywords: railway revenue management, dynamic programming, deterministic approximation, booking limits, bid price.

1. Introduction

In order to successfully deal with the pressure from competition, companies are using different methods and tools to improve business performance. Revenue management (RM) methods can help companies in determining optimal policies to allocate their capacity in a planning horizon and maximize revenue.

Over the last few decades, RM has been an area gaining attention of researchers and the area is still constantly evolving. Fields such as the hotel industry and air transportation made the largest contribution to the development of RM. These industries have attracted great attention of the academic community. Chiang et al. (2007) presented a survey of RM applications in different industries, and proposed future possible directions of research. On the other hand, there is still little published research on the railway transportation industry. This is probably due to the complexity of railway transportation organization and its specificity in terms of variable capacity and relatively unpredictable demand, especially in freight transport. Armstrong and Meissner

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(2010) recently provided an overview of the published literature regarding passenger and freight rail transportation RM, emphasizing the complexity of rail freight transportation.

Regarding capacity control, one of the fundamental decision is either to accept or reject an arriving booking request whilst taking into account the possibility of a more valuable demand arriving in subsequent time. In this paper, the possibility of implementation of this aggressive policy is observed in rail freight transportation, with special focus on Serbian national railway company. Serbian Railways have recently begun the process of reform, with the creation of three independent companies for infrastructure management, and passenger and freight transportation. The newly established company for freight transport, „Srbija Kargo", is faced with many challenges, such as the creation of an open market and the pressure of competition. Also, the reconstruction of the railway network on the Pan-European railway corridor 10 and increased demand for transport services will inevitably lead to application of new and effective methods in the field of RM.

In this paper, we consider the problem of railway freight operator providing a scheduled, cyclic, fixed capacity services on a linear network of yards on a given time horizon. The problem analyzed in this paper is inspired by the model „Periodic Train Capacity Allocation (independent periods)" developed in Campbell (1996). Taking into account available capacity, the problem is decomposed into discrete time periods and the impact of the current decisions on the future is evaluated. The proposed methodology for solving the problem is similar to those seen in truck transportation industry (Guerriero et al, 2009; 2012), adapted to the characteristics and specifics of the railway service considered in this paper. For solving this problem, a dynamic programming (DP) model is defined. Due to complexity and curse of dimensionality of the model, deterministic mathematical programming (DMP) approximation of DP is proposed. Based on the solution, booking limits and bid price controls to accept or reject a request at a certain time are defined.

The main contribution of this paper is a relatively simple and easy to solve model, which is based on DMP approximation of the DP problem, and which enabled defining two different booking policies. The DMP approximation allows implementation of the proposed policies in large instances, where DP formulation cannot be solved optimally, or would require excessive amount of time for solving. The deterministic approximation is selected instead of a probabilistic approach since it simplifies the problem of demand uncertainty by substituting it with its expectation. By going into the trade-off between the time required for solving the certain problem and the required level of accuracy in demand modeling, the model can be relatively easily extended to the probabilistic approach if needed.

Another contribution of this paper is the case study of a railway service provided by the Serbian railway freight operator, where the results of proposed booking policies are compared to that currently being implemented at Serbian railways. In facing situations when the demand exceeds the available capacity, the proposed methodology could be beneficial for the national freight operator in allocating its capacity in an effective way and maximizing profit.

This paper is organized as follows. Section 2 describes the problem observed. A DP formulation of the problem and its approximation are shown in sections 3 and 4, respectively. A case study of Serbian Railways rail freight service and numerical experiments results are presented in Section 5. Concluding remarks and future research directions are presented in Section 6.

2. Literature review

Revenue management applications are largely reported in the scientific literature which relates to the hotel and airline industries. However, models that deal with railway transportation have so far received very limited attention, especially in the rail freight transportation, probably due to the associated difficulties, such as heterogeneous and relatively unpredictable effective capacity

and future demand, as well as highly combinatorial character of capacity allocation and booking control models.

Armstrong and Meissner (2010) provided an overview of railway RM problems, both in passenger and freight transportation, where difficulties characterizing rail freight transportation are highlighted. By dividing rail freight into intermodal, general carload and unit train transportation, they provided a summary of RM models and included some possible extensions.

A recent survey on operations research applications in rail pricing and revenue management is also presented in Gorman (2015), focusing mainly on freight rail in the U.S., also giving possible future research directions and opportunities.

In her Ph.D. thesis, Campbell (1996) analyzed the application of booking and revenue management in intermodal freight transportation by developing a postponement Expected Marginal Revenue (pEMR) load acceptance policy in case of scheduled standard and premium intermodal services.

The integration of revenue and traffic flow management was analyzed in Kraft (2002), by decomposing the problem into the two multi-commodity network flow models for scheduling shipments already accepted and for forecasting future demands for which delivery appointments have yet to be scheduled. In contrast to this probabilistic approach at allocating future demand, where the probability customer accepts the service offer is observed in the model, our paper aims at controlling the booking control process by employing the aggressive booking policies, where requests are rejected by the carrier based on the deterministic model solution in case of unsatisfying booking limits or bid-price constraints.

Compared to Kraft (2002), Crevier et al. (2012) went a step further in integrating operations planning and revenue management in the rail freight transportation. They proposed a bilevel Mixed Integer Programming (MIP) formulation for integration of operations planning, such as car blocking and routing, as well as train scheduling with pricing decisions. In their approach, the carrier moves first to maximize its revenue, and the shipper moves second aiming to minimize the perceived disutility based on its attributes and the transport tariff.

In their study, Luo et al. (2016) analyzed a joint capacity leasing and demand acceptance problem in intermodal transportation. By formulating problem as a Markov Decision Process (MDP) with evolving supply and demand, the intermodal leasing and acceptance processes are modeled and the optimal policy is characterized. The importance of effective dynamic forecasting is emphasized.

Bilegan et al. (2015) considered the revenue maximization problem of a rail transport company or an intermodal operator that sells transport services to the market. In their paper, inspired by bid-price capacity control mechanisms, a load acceptance problem was formulated as two network flow models that maximize expected revenue for the case where a particular demand is accepted and for the case when it is rejected. The decision on accepting or rejecting an arriving transport order is then based on the difference in expected revenue between these two scenarios. The proposed approach is based on a probabilistic MIP model formulated on a space-time network representation of the transportation service. Additionally, they introduced four different fare classes as a combination of two categories for booking anticipation and two categories for maximum delivery time. As opposite to their bid-price based approach that requires solving two different probabilistic MIP models, the bid-price policy (BPP) as well as the booking limits policy (BLP) defined in this paper are obtained from solving a single DMP model.

Van Riessen et al. (2017) further analyzed the effects of the fare classes definition and incorporation in the intermodal transportation. They proposed the Cargo Fare Class Mix (CFCM) problem, which aims to set booking limits for each fare class at a tactical level, so the expected revenue is maximized, while considering the available capacity at the operational level.

Wang (2016) considered the stochastic resource allocation problem for containerized cargo transportation with uncertain capacities and network effects, in which a freight operator needs to allocate a certain amount of capacity to each product to maximize the expected profit. The problem is formulated as a constrained stochastic programming model. An approximation model of the problem is built and a sampling based algorithm to solve the approximation model is proposed.

Wang et al. (2017) defined a dynamic resource allocation problem, aiming to determine the policy for an intermodal operator which provides optimal quantities of each service product allowed to be sold during each time of the horizon observed. Similarly to the work of Luo et al. (2016), the problem is formulated as a Markov Decision Process (MDP) and several approximations of MDP are developed. The importance of dynamic decisions and stochastic demand is emphasized.

The contribution of this paper is the booking control system based on a simple and easy to solve mathematical programming model. Starting from a dynamic programming (DP) formulation, a deterministic mathematical programming (DMP) approximation of the DP is proposed, enabling implementation of two different booking control policies – based on booking limits (BLP) and bid prices (BPP). By observing the problem of railway freight operator providing a scheduled, cyclic, fixed capacity service on a linear network of yards on a given time horizon, the proposed model can easily be extended to the problem of intermodal freight service.

3. Problem description

This section describes the service offered by the railway company, booking process, current practice, as well as some assumptions made in this paper. The problem considered is inspired by the service observed in Campbell (1996).

3.1 Railway service and booking process
We consider a regular and cyclically scheduled *service* with fixed composition (Bilegan et al., 2015). The service consists of a single train with fixed composition, scheduled cyclically over the finite time horizon, denoted as the „operating horizon", on a linear network of yards. The route of a service consists of a set of *legs*, where each leg represents an arc connecting two adjacent yards in the psychical network. The service is made up of number of *blocks* with different origin and destination, where each block represents a set of freight cars temporarily joined during the trip between common origin and destination (Kraft, 2002). Each block is characterized with its capacity and departure time from its origin. For the illustration of the problem observed, Figure 1 shows a graph representation of a hypothetical physical railway network with four consecutive yards, and its corresponding service made up of four blocks with different origin-destination pairs.
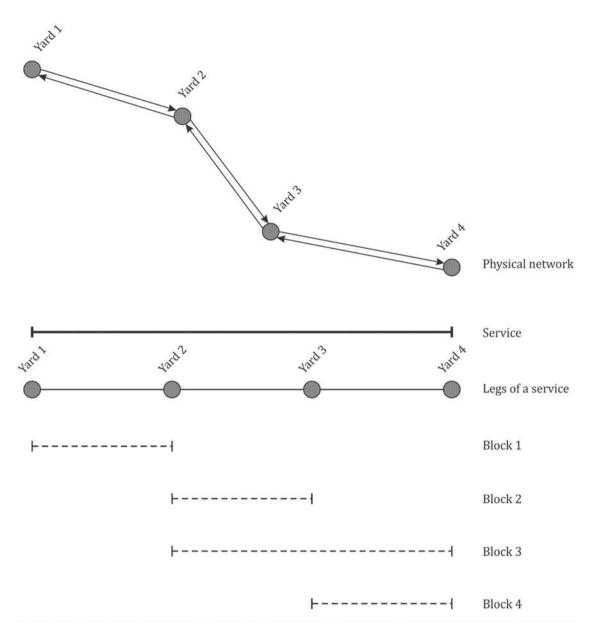
Figure 1. Representation of a railway network and service

The complexity of the mathematical programming model is affected by the constraints involved. In modeling allocation of capacity in railway problems, certain constraints are imposed representing the requirements that have to be met, e.g. not exceeding the available capacity. Regarding the capacity constraints, there are different approaches in the literature, based on the problem observed and network specification. Common capacity constraints include maximum train capacity, legs and blocks capacity (e.g. Bilegan et al., 2015; Campbell, 1996; etc.). Similar to the maximum legs capacity, Kraft (2002) defined the train segments capacity constraints, where each segment represents the route part between two consecutive set-offs or pick-ups. In this case, the train segment may include number of legs, i.e. if the route part between two consecutive set-offs or pick-ups covers two or more successive legs, and where the maximum train segment capacity would depend on the lowest maximum capacity leg within the route part. In this paper, we observe the fixed composition and fixed capacity service, and assume that the constraints regarding legs and train capacity are satisfied with blocks capacity constraints imposed, i.e. the

total maximum blocks capacity within the service does not exceed legs capacity within the service route.

This paper concerns an irregular demand. The regular demand, which is already allocated on the network, is not included in the analysis. The regular demand is usually subject of long-term contracts between clients and railway company, and is processed with special prices. Considering the uncertainty and great variation of demand across locations and time characterizing rail freight transportation, the existence of a reservation system is imposed. The booking requests arrive sequentially over the finite time horizon, denoted as the „booking horizon", and are processed in the order of their arrival by an accept/reject booking RM system proposed. Each booking request is characterized with its origin and destination (i.e. corresponding block within the service), type of a request, freight volume (in freight cars), and departure time. Only requests concerning predefined blocks (origin-destination pairs) can be placed to the railway operator. In practice, blocks within the service are predefined by the blocking plan, at the tactical planning level. RM policies are implemented in order to dynamically accept or reject arriving booking requests, at the operational level, with the aim of revenue maximization.

3.2 Current practice

The current practice applied by the Serbian national railway company is similar to the traditional practice widely present, where the transportation requests are accepted on a first-come first-served (FCFS) basis, with the only limitation of free capacity existence. The prices are usually based on the operational and handling costs, quantities and distances. The typical example of unsatisfying transportation requests due to a scarce capacity in case of the Serbian railway company is the grain transportation, during the peak of a season. Similar to this example, during some periods, some high-value demands may be rejected due to infeasibility. Regarding that, it can be discussed that holding some capacity in reserve would be advantageous, if there is a reasonable expectation that high revenue customers will arrive later (Bilegan et al., 2015).

On the other hand, it can be argued about the acceptability of the principle that the transportation demand can be rejected in practice. Regarding this matter, there are great differences between national rail industry organizations. For example, large railroads in the U.S. are forced to accept any transport demand placed to them, as a consequence of „common carrier laws" (Bilegan et al., 2015; Gorman, 2015). Considering the Serbian railway company, the regulations and practice are similar to those of the most EU countries. There are no such strict obligations as in the U.S. According to the Serbian Law on Railway[4], the railway operator is obliged to offer the same conditions and tariffs prescribed by the Law, regardless of who the client is. Although, taking into account that the railway transportation is of general social interest, the principle of rejecting transportation demands may not be acceptable in all contexts, the assumptions made in this paper and the model developed have the goal of analyzing the possible benefits of implementing this kind of discrimination policies.

The next section describes a DP formulation for the cyclic train service problem (CTSP). The DP formulation is inspired by the truck rental problem (TRP) observed in Guerriero et al. (2012).

4. A dynamic programming formulation for the CTSP

We consider a problem of railway operator providing a regular, cyclic service during the finite operating horizon on a given linear network of yards. The service is consisted of number of blocks for which the booking requests are placed during the booking horizon. At each time of the booking horizon, the railway operator has to decide to either accept or reject arrived

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[4]Law on Railway ("Official Gazette of the Republic of Serbia " No. 45/2013, 91/2015)

transportation requests, with the aim of profit maximization, taking into account the available capacity and the fact that complete information about future demand is unavailable.

Define the following:

N – The set of nodes representing yards on a linear service network (train route).

B – The set of blocks denoted as $(i,j) \in B$ where $i,j \in N, i \neq j$.

K – The set of request types denoted as $k \in K$, where each type includes different operational and handling costs, and thus different revenue obtainable.

q – The quantity of a request (in freight cars), where $q = \{1,...,q_{max}\}$.

Time is discrete. Booking horizon consists of T time units (TUs) denoted as t, and operating horizon consists of $\overline{T}$ TUs denoted as $\overline{t}$, where $t = 1,...,T$ and $\overline{t} = 1,...,\overline{T}$. It is assumed that the booking and the operating horizon do not overlap. Regarding periods between time steps, they can take values up to several hours (e.g. 3, 6 or 12 hours) depending on different factors, such as operating characteristics and data granularity.

The state of the system is described by a matrix $X = \left[x_{ij}^{\overline{t}} \right]$, $X \in \square^{B \times \overline{T}}$, where each element of the matrix $x_{ij}^{\overline{t}}$ represents the available (free) capacity of the block $(i,j) \in B$ at time $\overline{t} = 1,...,\overline{T}$. Regarding the capacity, it is assumed that the minimum capacity needed for service operation is ensured by the regular flows already allocated, which are subject of long-term contracts, and which are not observed in the model. Thus, the remaining capacity is taken into account regarding the constraints in the model. The available capacity $x_{ij}^{\overline{t}}$ is thus between zero (when there is no capacity available for arriving requests) and an upper bound (Bilegan et al., 2015).

In each time period t, at most one transportation request of type $k \in K$ and quantity $q = \{1,...,q_{max}\}$ for each block $(i,j) \in B$ and each departure time $\overline{t} = 1,...,\overline{T}$ can arrive. This means that the time periods within discrete horizon are assumed sufficiently short that two or more identical requests, i.e. of an identical type and quantity, and for an identical block and departure time cannot arrive in the same time. Let $\lambda_{ij\overline{t}kq}^{t}$ denote the probability that at time t one transportation request of type $k \in K$ and $q = \{1,...,q_{max}\}$ units (freight cars) for block $(i,j) \in B$, with departure time $\overline{t} = 1,...,\overline{T}$ is made. If $\lambda_0^t = 1$ represents the probability that no request arrive at time t, it holds that $\sum_{k \in K} \sum_{q=1}^{q_{max}} \lambda_{ij\overline{t}kq}^{t} + \lambda_0^t = 1$ for each $\overline{t} = 1,...,\overline{T}$ and $(i,j) \in B$.

Let the boolean variable $u_{ij\overline{t}kq}^{t}$ takes value 1 if the transportation request of type k and q units for block $(i,j) \in B$ with departure at time $\overline{t}$, is accepted at time t, and 0 otherwise.

Let R_{ij}^{k} be the per unit revenue obtained by satisfying the transportation request of type $k \in K$ for block $(i,j) \in B$.

The Bellman equation for $V_t(X)$ is:

$$V_t(X) = \sum_{k \in K} \sum_{q=1}^{q_{max}} \lambda_{ij\overline{t}kq}^{t} \max_{u_{ij\overline{t}kq}^{t} \in \{0,1\}} \left[qR_{ij}^{k}u_{ij\overline{t}kq}^{t} + V_{t+1}(\tilde{X}) \right] + \lambda_{ij0kq}^{t}V_{t+1}(X) \tag{1}$$

where:

- $\tilde{x}_{ij}^{\overline{t}} = (x_{ij}^{\overline{t}} - qu_{ij\overline{t}kq}^{t})$, $\overline{t} = 1,...,\overline{T}, (i,j) \in B$. This term updates the capacity on block $(i,j) \in B$ with departure time $\overline{t} = 1,...,\overline{T}$ when a certain request is accepted.

- $\tilde{x}_{rs}^{\bar{\tau}} = x_{rs}^{\bar{\tau}}$, $\bar{\tau} \neq \bar{t}$, $(r,s) \neq (i,j) \in B$. This term updates the capacity on the rest of the system when a request for block $(i,j) \in B$ with departure time $\bar{t} = 1,...,\bar{T}$ is accepted.

The boundary conditions of the Bellman equation are:

$$V_t(0) = 0, \ \forall t$$

$$V_t(X) = -\infty, \ \text{if } x_{ij}^{\bar{t}} < 0 \text{ for some } \bar{t}, (i,j) \in B; \forall t$$

$$V_{T+1}(X) = 0, \ \text{if } x_{ij}^{\bar{t}} \geq 0 \ \forall \bar{t}, (i,j) \in B$$

$$V_{T+1}(X) = -\infty, \ \text{if } x_{ij}^{\bar{t}} < 0 \text{ for some } \bar{t}, (i,j) \in B$$

Due to the curse of dimensionality, the proposed DP model is unlikely to be solved optimally. Thus, a deterministic approximation of the DP is proposed in the next section, based on approximations by the deterministic mathematical programming (DMP) (de Boer et al., 2002; Williamson, 1992).

5. A deterministic mathematical programming formulation for the CTSP

In the DMP approximation, stochastic quantities are replaced by their mean, and the capacity and demand are assumed to be continuous (Guerriero et al., 2009; 2012).

Define the following:

- d – The random cumulative future demand at time t, and $\bar{d}$ its mean. In particular, $d_{ij}^{\bar{t}kq}$ represents the aggregate number of requests of type $k \in K$ and quantity $q = 1,...,q_{max}$ for block $(i,j) \in B$ with departure time $\bar{t}$.

- $y_{ij}^{\bar{t}kq}$ – The number of requests of type $k \in K$ and quantity $q = 1,...,q_{max}$ to be assigned to the block $(i,j) \in B$ with departure time $\bar{t}$.

- R_{ij}^k – The revenue obtained by satisfying the transportation request of type $k \in K$ for block $(i,j) \in B$. This revenue is proportional to the distance between i and j.

- $x_{ij}^{\bar{t}}$ – The available capacity (in freight cars) for the block $(i,j) \in B$ for the departure time $\bar{t} = 1,...,\bar{T}$.

The total revenue obtainable for the service at time t, with the system capacity x, can be calculated by solving the following MIP problem:

$$R^{CTSP}(x,t) = \max \sum_{\bar{t}=1}^{\bar{T}} \sum_{(i,j) \in B} \sum_{k \in K} \sum_{q=1}^{q_{max}} q R_{ij}^k y_{ij}^{\bar{t}kq} \tag{2}$$

subject to

$$y_{ij}^{\bar{t}kq} \leq \bar{d}_{ij}^{\bar{t}kq} \quad, \forall \bar{t}, (i,j) \in B, k, q \tag{3}$$

$$\sum_{k=1}^{K} \sum_{q=1}^{q_{max}} q y_{ij}^{\bar{t}kq} \leq x_{ij}^{\bar{t}} \quad, \forall \bar{t}, (i,j) \in B \tag{4}$$

$$y_{ij}^{\bar{t}kq} \geq 0 \text{ and integer} \quad, \forall \bar{t}, (i,j) \in B, k, q \tag{5}$$

In case when the number of decision variables and constraints is large, as in the real-world situations with large network and service configurations, the MIP problem might be hard to solve. Different heuristic algorithms could be used in solving this problem. Regarding e.g. airline networks, it is common practice to solve LP relaxation (DLP) rather than MIP problem. In particular, with the assumption of integer capacity values, and integer demand expectations, the DLP formulation yields to an integer optimal solution, without the need of explicitly enforcing this as a constraint (de Boer et al., 2002).

Regarding the problem observed in this paper, where at most one request of each type and quantity may arrive in each period of the booking horizon, and by imposing integer capacity values, the RHS values of constraints (3) and (4) are also integers. In particular, in MIP formulation, the decision variable $y_{ij}^{\bar{l}kq}$ can take values 0 or 1, but due to the existence of parameter q in constraint (4), in case of DLP formulation the decision variable can also take non-integer values between 0 and 1. In this paper, we will apply this simple DLP formulation, where the request will be rejected if the decision variable takes value less than 1, since requests cannot be partially accepted. This may lead to a certain error and decrease in total revenue obtainable, which will be evaluated through the comparison of results with results obtained from the MIP problem. More sophisticated methods for solving this problem are being left for future research.

There are various ways in implementing booking control. By solving the DLP model, the primal variables can be used to construct a partitioned booking limits control directly, or the dual variables to define a bid-price control (Guerriero et al., 2009; 2012; Talluri and van Ryzin, 1998; 2004). Regarding the booking limits control, the booking requests are rejected if the respective booking limits, which are imposed by the respective constraints in the model, would be exceeded in case of accepting given requests. The bid-price control represents an alternative form of booking control which is derived from the dual variables associated with the respective resource capacity constraints. In this case, bid-prices are linked to each block within the service and over the observed time horizon, and no requests are accepted for the respective block at a certain time unless the revenue obtainable exceeds its bid-price.

In this paper, the partitioned booking limits policy (BLP) as well as the bid price policy (BPP) are defined in order to dynamically accept or reject arriving booking requests. At each time of the booking horizon, the $R^{CTSP}(x,t)$ is solved and the solution is used in decision making. Since at most one request of each type and each quantity may arrive within one time interval of the booking horizon, the primal decision variables $y_{ij}^{\bar{l}kq}$ in the BLP policy are limited to the value 1.

Based on the solution, regarding the BLP policy, each request for which the decision variable takes value 1 is accepted, the available capacity of respective block is updated by subtracting its capacity before accepting the request with the quantity associated with the given request, and the revenue obtained from accepting the request is calculated. Otherwise, the request is denied. The BLP algorithm has the following form.

BLP Algorithm

Solve $R^{CTSP}(x,t)$. Let $y_{ij}^{*\bar{t}kq}$ denote its optimal solution.

> FOR ($\bar{t} = 1,...,\bar{T}$ AND $(i,j) \in B$ AND $k \in K$ AND $q = 1,...,q_{max}$) DO
>> IF $y_{ij}^{*\bar{t}kq} = 1$ THEN
>>> ACCEPT the request;
>>> UPDATE appropriately the capacity:
>>>> $$\tilde{x}_{ij}^{\bar{t}} = (x_{ij}^{\bar{t}} - q)$$
>>> CALCULATE the revenue obtained from accepting the request;
>> ELSE
>>> DENY the request.
>> END IF
> END FOR

The proposed model can be easily extended to the case when multiple requests of each type and each quantity may arrive within one time interval of the booking horizon. This can be done by setting the condition for accepting the request as $y_{ij}^{\bar{t}kq} > 0$ instead of $y_{ij}^{\bar{t}kq} = 1$, and by updating the value of decision variable each time a request is accepted by setting $y_{ij}^{\bar{t}kq} = y_{ij}^{\bar{t}kq} - 1$.

Another approach in making accept/reject decisions is by using the bid price control policy. Basically, bid price represents an estimate of the marginal cost of consuming the next incremental unit of the resource capacity (Guerriero et al., 2012). In the BPP algorithm, $R^{CTSP}(x,t)$ is solved at each time of the booking horizon, and based on the dual variables $\pi_{\bar{t}}^{ij}$ associated with the capacity constraints (4) the decision of accept/reject request is made. If the unit revenue of accepting the certain request of type k for block $(i,j) \in B$ is greater than or equal to the bid price $\pi_{\bar{t}}^{ij}$ of respective block departing at respective time $\bar{t}$, and if the quantity consisting the request do not exceed the available capacity $x_{ij}^{\bar{t}}$, the request is accepted. The capacity of respective block is then updated in the same way as in the BLP algorithm, and the revenue obtained from accepting the request is calculated. Otherwise, the request is rejected. The BPP algorithm has the following form.

BPP Algorithm

Solve $R^{CTSP}(x,t)$ to obtain the dual variables $\pi_{\bar{t}}^{ij}$, $\bar{t} = 1,...,\bar{T}, (i,j) \in B$.

> FOR ($\bar{t} = 1,...,\bar{T}$ AND $(i,j) \in B$ AND $k \in K$ AND $q = 1,...,q_{max}$) DO
>> IF $R_{ij}^k \geq \pi_{\bar{t}}^{ij}$ AND $x_{ij}^{\bar{t}} \geq q$ THEN
>>> ACCEPT the request;
>>> UPDATE appropriately the capacity:
>>>> $$\tilde{x}_{ij}^{\bar{t}} = (x_{ij}^{\bar{t}} - q)$$
>>> CALCULATE the revenue obtained from accepting the request;
>> ELSE
>>> DENY the request.
>> END IF
> END FOR

The proposed policies are applied to the railway service provided by the Serbian national railway operator, and the results of numerical experiments are presented in the next section.

6. Case study

The model and policies described in the previous section are applied on a cyclic train service operating on the Serbian national railway network by using simulated data. The model (2)-(5) is developed, the BLP and BPP algorithms are defined, and all other computational experiments are performed in AIMMS 4.24 software[5], with CPLEX 12.6 as solver, on a PC with Intel Core i3-4005U CPU, 1.7GHz. The values of parameters in model (2)-(5) are adopted and generated as will be described in Sec. 6.1. Bottlenecks are imposed by setting the available capacity scarce compared to the volume of requests arriving. The simulations are carried out by implementing the booking policies concerning the booking and operation horizons defined. In each simulation run, the requests are generated and are processed in each time of the booking horizon. The results are compared to the policy FCFS currently implemented by the Serbian rail freight operator with the aim of assessing the possible benefits of applying these aggressive discriminatory policies.

6.1 Service description and input data

We consider a service provided by the Serbian railway freight operator on the railway line Belgrade-Novi Sad-Subotica, a part of the Pan-European corridor 10 (Figure 2). The Pan-European corridor 10, which connects Salzburg in Austria and Thessaloniki in Greece, and which passes through Slovenia, Croatia, Serbia and Macedonia, is one of the Pan-European corridors defined at the second Pan-European transport conference held in Crete in 1994, followed by the third conference in Helsinki, in 1997. Encompassing 2.528 km of railway lines in total, its overall objective is to promote sustainable and efficient transport systems, thru reconstruction and rehabilitation of main lines in this part of Europe (European Committee of the Regions, 1998).

The railway line observed in this paper represents the most congested line on the national network, with the large demand sources in Belgrade and Novi Sad, and Subotica which is the border yard to Hungary and the EU.
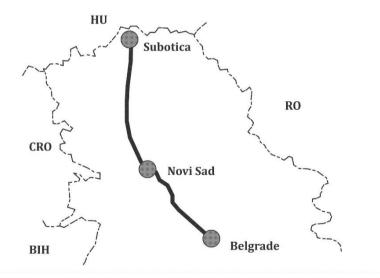

Figure 2. Physical service network

Legs of a service and blocks defined within the service provided are presented in Figure 3. The service consists of three blocks, covering all possible origin-destination pairs within the network.
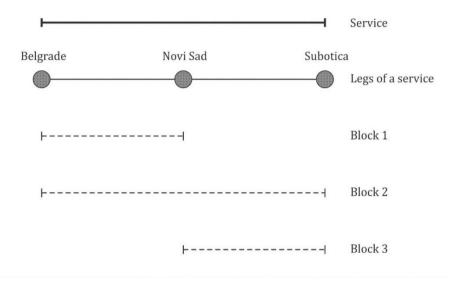

Figure 3. Legs and blocks of a service

For the better understanding of how the service operates during the operating horizon, Figure 4 shows three successive trains on a space-time network, in terms of blocks. Time periods in the operating horizon are equal to the time intervals between two consecutive departures.
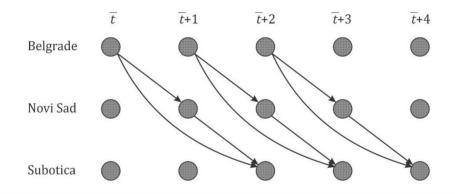

Figure 4. Service representation in terms of blocks during the operating horizon

Time is discrete. We observe the finite operating horizon of 7 TUs, thus $\bar{t} = 1,...,7$. The booking requests arrive to the system and are threated sequentially, in the order of their arrival. The booking horizon is discrete, consisting of 2 TUs. At each TU of the booking horizon, for each block $(i,j) \in B$ and each TU of the operating horizon, a single booking request of type k and quantity q is generated. There are three types of demand, with different unit revenue obtainable. Maximum quantity that can be consisted within a request is $q_{max} = 5$ freight cars. Unit revenue obtainable by accepting a request is defined as $R_{ij}^k = r_k L_{ij}$, where L_{ij} represents the length of route for respective block, and coefficient r_k is assigned values 0.8, 1 and 1.2 for each of three demand types, respectively.

In order to obtain consistent results, the simulation process for each policy is repeated 100 times, and the average values obtained are compared. In each simulation run, the available capacity $x_{ij}^{\bar{t}}$

for each block and each departure time is randomly chosen from the interval {5,…,10}, and the demand is generated by using Binomial distribution, e.g. $d_{ij}^{\bar{l}kq} \sim Binomial(p = 0.2, n = 1)$. The available capacity is scarce compared to the volume of requests arriving, thus rejecting some requests is inevitable.

In addition to the policies defined, the FCFS policy is included, based on the current practice at Serbian Railways. Regarding the FCFS model, the requests are threated one by one in the order of their arrival and are accepted only if they satisfy the available capacity constraints, irrespective of their profitability. Also, the deterministic optimal solution policy (DET) is included, where the perfect information of complete future demand is available, and the decisions of either accept or reject requests are made in a pure optimal way (Bilegan et al., 2015). It has been shown that the objective function of DET policy overestimates the expected revenue obtained by implementing its solution as an actual booking limit policy, and that it provides an upper bound of an actual revenue obtainable. (Madansky, 1960; deBoer et al., 2002). The DET policy optimal solution is obtained by generating total future demand and by solving R^{CTSP}.

6.2 Results

Based on the procedure defined, the implementation of each policy is simulated 100 times and the results are compared. The average results for each policy are presented in Table 1. The results include average total revenue (ATR) obtained and its 95% confidence interval (ATRCI), average percent of rejected demand (APRD), and an average revenue per demand (ARPD) obtained. Regarding the relevance of the measures provided, it could be argued that the ATR represents the most important indicator, considering that revenue maximization is the main goal of each railway freight operator. The ATRCI can provide railway operators insight in reliability of a certain policy in terms of the variations in total revenue obtainable. Taking into account general social interest associated with railway transportation, the great significance of the APRD indicator can be assumed, especially in case of large, monopolistic, national freight operators, since rejecting the requests will most likely affect the modal shift in favor of less efficient road transport. Giving priority to the ARPD indicator can be assumed in case of small or regional freight operators with scarce resource capacities, and which tend to transport as much valuable shipments as possible.

Table 1. Results of different policies

Policy	Indicator			
	ATR	ATRCI	APRD	ARPD
BLP MIP	17946.93	[17747.42, 18146.43]	57.50	341.40
BLP LP	16890.68	[16653.18, 17128.17]	58.16	324.83
BPP	16211.46	[16011.96, 16410.96]	56.78	301.07
FCFS	16030.15	[15816.86, 16243.45]	59.01	314.43
DET	19408.81	[19232.15, 19585.47]	56.84	361.88

Regarding the total revenue obtained and the two policies defined in this paper, both policies gave better results compared to the standard FCFS policy. The highest performance showed the BLP policy solved as MIP problem. The LP formulation of this problem gave lower results, as well as the BPP, but still showed better performance than the FCFS policy, which has the lowest average value of the total revenue obtained. The FCFS policy also has the highest average percent of rejected requests. Although having the lowest ARPD value, the BPP showed better performance in all other aspects compared to the FCFS. Both MIP and LP formulation of the BLP gave significantly higher ARPD compared to the FCFS.

Based on the results, it can be concluded that the DET policy, where the complete information about future demand is available, gives an upper bound and provides maximum revenue obtainable by the given service. Off course, this is an ideal situation, and hardly achievable, taking into account the uncertainty of future demand in rail freight transportation.

Additionally, in order to compare performance of the BLP and BPP with standard FCFS and DET policies, two indicators, average percentage gain (APG) and average percentage error (APE), are introduced (Guerriero, 2012). These two indicators are based on comparing the average revenues obtained from respective models, and are defined as follows:

$$APG = \frac{R_i - R_{FCFS}}{R_{FCFS}} \times 100, \quad i = BLP\ MIP, BLP\ LP, BPP \tag{6}$$

$$APE = \frac{R_i - R_{DET}}{R_{DET}} \times 100, \quad i = BLP\ MIP, BLP\ LP, BPP \tag{7}$$

The values of APG and APE indicators are presented in Table 2.

Table 2. Average percentage gain and average percentage error of proposed policies

Policy	Indicator	
	APG	APE
BLP MIP	11.96	-7.53
BLP LP	5.37	-12.97
BPP	1.13	-16.47

Regarding the APG indicator, which measures the gain in revenue obtained by the policies defined compared to the FCFS policy, both policies showed positive gain in revenue. The best performance showed the BLP formulated as an MIP problem with the APG equal to 11.96%, while regarding the LP formulation of this policy the gain is 5.37. Although the BPP has the lowest APG value, the gain of 1.13% percent represents significant improvement, taking into account the total volume of freight flows on the national network, which produce millions of dollars or euros revenue per year.

Considering the APE indicator, which concerns the error between revenue obtained from the two defined policies and the ideal case when perfect information is available, the negative value indicates decrease in revenue obtained from the BLP and BPP. As in the previous case, the MIP formulation of BLP showed the lowest deviation from the ideal case, with the APE value equal to -7.53%. The LP formulation of BLP gave the APE equal to 12.97, while the lowest performance showed the BPP with APE equal to 16.47%.

7. Conclusions and future research

In this paper the implementation of aggressive discriminatory policies in rail freight transportation is analyzed, aiming to evaluate the possible benefits, compared to the standard FCFS principle currently implemented by the Serbian national rail freight operator. The problem is formulated via dynamic programming, and the deterministic approximations are used in order to obtain simple and easy to solve models. Two discriminatory policies, the booking limits policy (BLP) and the bid price policy (BPP), are defined and applied on a relatively simple case of a regular, cyclic, single train service on the Serbian national rail network. Using simulated data, the results showed potentially great benefits compared to the FCFS policy. Although not acceptable in all contexts, in cases when the demand greatly exceeds available capacity, these policies may

be an effective tool for business performance improvement, in terms of effective capacity allocation and revenue maximization.

This study represents the starting point to the development of a dynamic booking system which will take into account more realistic rail freight transportation service conditions and constraints. The overcoming of limiting assumptions made in this paper will include multiple services network and possibility of block swaps, shipment switching and connections. Also, the introduction of additional constraints concerning train capacity and legs (train segments) capacity will be studied. Regarding transportation requests and demand, the possibility of departure and delivery time choice will be introduced, as well as fare classes based on different criteria.

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