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A Revenue Management Approach for Network Capacity Allocation of an Intermodal Barge Transportation System

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Abstract. We propose a revenue management (RM) model for the network capacity allocation problem of an intermodal barge transportation system. Accept/reject decisions are made based on a probabilistic mixed integer optimization model maximizing the expected revenue of the carrier over a given time horizon. Probability distribution functions are used to characterize future potential demands. The simulated booking system solves, using a commercial software, the capacity allocation problem for each new transportation request. A conventional model for dynamic capacity allocation considering only the available network capacity and the delivery time constraints is used as alternative when analyzing the results of the proposed model.

Keywords: Revenue management, network capacity allocation, intermodal barge transportation, probabilistic mixed integer model.

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1 Introduction

Barge transportation offers a competitive alternative for freight transportation, complementing the traditional road and rail modes. Moreover, considered as sustainable, environment-friendly and economical, barge transportation has been identified as instrumental for modal shift and the increased use of intermodality in Europe [3]. Yet, studies targeting barge transportation are scarce, (e.g., [4, 6, 7, 8, 11, 14]), the ones considering the intermodal context being even more rare (e.g., [13, 15, 18, 17]). An important and recent review of the scientific literature on multimodal freight transportation planning can be found in [12].

Revenue Management (*RM*), broadly used in passenger transportation to manage trip prices and bookings (e.g., [1]), has been identified as a desirable feature for freight transportation, including barge intermodal services [15]. RM is expected to provide freight carriers with tools to better manage revenues and enhance service by, in particular, tailoring the service levels and tariffs to particular classes of customers. In [16], the authors study revenue management in synchromodal container transportation to increase the revenue of the transportation providers. In their study, several delivery types are provided by carriers. Each type of delivery is associated with a fare class, characterized by a specific price and a specific due time. In [9], authors propose a cost-plus-pricing strategy to determine the price of delivery types in the context of intermodal *(truck, rail and barge)* freight transportation. The price associated with each delivery type is the sum of the operational cost and the targeted profit margin. The price of a delivery type depends on its urgency as well.Different scenarios, i.e., self-transporting, subcontracting, and a mix of the two are studied, with different operational costs and targeted profit margins. However, in both [16] and [9], only one type of customers, who sign long-term contracts with the carriers, is considered. Consequently, no accepting or rejecting decision is made during the operational phase. In [10], customers are classified into two categories: contract sale (large shippers, which might be considered regular) customers, and free sale (scattered shippers) customers. A two-stage stochastic optimal model is then proposed to maximize the revenue. In the first stage, the revenue is maximized serving contract sale customers only. In the second stage, the slot capacity after serving contract sale customers is used to serve the scattered shippers customers through a dynamic pricing method for price settling and an inventory control method for slot allocation applied jointly in each period of free sale. The exploration of RM-related issues in freight transportation is still at the very early stages, however, as illustrated by the reviews related to air cargo operations [5], railway transportation [1], and container synchromodal services [15].

We aim to contribute to the field by proposing a RM model to address the network capacity allocation problem of an intermodal barge transportation system. As intermodal barge and rail systems share a number of characteristics, e.g., scheduled services, limited transport capacity (resource) and uncertain future demands, the approach is inspired by the work of [2] where the authors develop a model to dynamically allocate the rail capacity at operational level. In defining the revenue management problem for barge transportation we induce novel features to our modeling, however: we adapt it for the barge transportation space-time network, we enrich it by introducing different categories of customers with the definition of specific treatment for each of them, including particular accept/reject rules. An important feature offered by the new modeling lays in the proposal of a negotiation process based on the optimisation model when dealing with rejected demands, as explained in more details further on. Customers are classified into different categories as follows. Regular customers, who sign long-term contracts with the carriers/providers, must be satisfied and thus all these regular category of demands have to be accepted. On the other hand, the so called spot-market customers, who request transportation less frequently and on an irregular basis, may be rejected if needed. The accept/reject mechanism is settled according to an estimation of the profitability of each new incoming demand, given the availability of service capacities at the time of decision. In order to better consider customer behavior specificities, those spot-market customers are further classified into partially-spot customers, who would accept their requests to be partially accepted, and fully-spot customers, whose requests must be either accepted as a whole or not accepted at all. These acceptance rules are introduced and used in the new RM model (through specific decision variables). Moreover, based on the customer differentiation, and on the associated acceptance rules, different mechanisms are set out in a new negotiation process model which is implemented and used when dealing with rejected demands. At the authors best knowledge, this is the first contribution proposing to introduce RM techniques, e.g., price differentiation and customer classification, at the operational level planning of barge transportation activities.

The application of RM strategies requires a booking system to manage transport requests, and the capability to forecast future demands. In our case, the simulated booking system performs an accept/reject decision for each new transport request, based on the results of the proposed optimization model maximizing the expected revenue of the carrier over a given time horizon. In case of acceptance, the corresponding optimal routing is also provided by the optimization. Probability distribution functions are used to characterize future potential demands for transportation and, thus, the proposed optimization model takes the form of a *probabilistic mixed integer program* (MIP). A commercial solver is used to address this model. Simulation is used to analyze the performance of the proposed optimization model and RM strategies, through comparisons with a conventional dynamic capacity allocation model considering only the available network capacity and the delivery time constraints.

The remainder of this paper is organized as follows. We briefly describe the network capacity allocation problem and the considered RM concepts and strategies for intermodal barge transportation in Section 2. The proposed RM model is introduced in Section 3. Simulation and numerical results are discussed and analyzed in Section 4. We conclude in 5.

2 Problem Characterization

We first briefly present the general problem of dynamic capacity allocation for barge transportation. The mechanisms of the booking system are then discussed, together with the proposed RM strategies. The associated notation is identified as well.

2.1 Dynamic Capacity Allocation Problem

Consolidation-based carriers, such as those operating barge services, plan and schedule their operations for the "next season" with the goal of jointly maximizing the revenue and satisfying the forecast regular demand, through efficient resource utilization and operations. Transport requests fluctuate greatly during actual operations, however, in terms of origins, destinations, volumes, etc., not to speak of those unforeseen demands the carrier will try to accommodate. The capability to answer customer expectations of the transport network is consequently continuously changing as well, together with its efficiency and profitability. Setting up some form of advanced booking system is the measure generally adopted to handle this complex situation.

Transport booking requests are traditionally answered on a first-come first-serve (FCFS) basis. Moreover, a transport request is (almost) always accepted provided the network currently has the capability to satisfy both the volume and the delivery time specified by the customer. This has the unwanted consequence that requests coming at a latter time might not be accepted, even though they present the potential to generate a higher revenue, due to a lack of transport capacity, resulting in the loss of additional revenue for the carrier.

RM-based booking systems operate according to different principles. The booking system considered in this paper manages the transport capacity, and the decision to accept or reject a new demand, considering a set of potential future demands characterized by different fare classes. To make the final decision, the acceptance and rejection of the current demand are compared by optimizing the estimated total revenue of all demands, current and potential future ones. Therefore, in our model, a current transport request may be rejected if it appears less profitable compared with the estimated profit of future demands competing for the transport capacity. The resource is then reserved for the future demands, expecting a higher total revenue. On the other hand, when the booking system accepts the current transport request and more than one possible routing exist, a "better" capacity allocation plan can be obtained by considering the future demands. That is, the capacity available in the future might more closely match future demands, increasing the possibility of acceptance and the generation of additional revenue.

We formulate the dynamic capacity allocation problem on a space-time network over a time interval composed of $1, ..., T$ time instants. The nodes of the $G = (N_{IT}, A)$ network are obtained by duplicating the representation of the physical terminals at all time instants, i.e., a node $n(i,t) \in N_{IT}$ specifies the physical terminal i and the time instant t.

A set of already-selected services, each with given schedule, route and capacity, provides transportation among the nodes in N_{IT}. Note that, in this research, we assume that services have already been scheduled at the tactical planning level (i.e., when the Scheduled Service Network Design problem is solved) and are not to be rescheduled at the operational level. The capacities of scheduled services are also fixed since vehicles are already assigned to services and no extra-vehicles are considered to be available upon request. A service $s \in S$ is characterized by its transport capacity $cap(s)$ and set of legs $\eta(s)$. Leg $l \in \eta(s)$ represents a path between two consecutive stops of service s, and is characterized by its origin and destination terminals, $o(l), d(l) \in N_{IT}$, with the respective departure $t_{dep}(l)$ and arrival $t_{avl}(l)$ times. Let $s(l)$ and $cap(l) = cap(s(l))$ identify the service it belongs to and its capacity, and define $cap\_avl(l)$, the residual capacity of leg l after having routed the already accepted demands.

The set of arcs A is then made up of the sets A_L and A_H representing the transport and holding arcs, respectively. Set A_L is composed of all the defined service legs, while A_H arcs link two representations of the same terminal at two consecutive time periods. Holding arcs represent the possibility of demand flows to wait at their respective origins or at intermediate terminals during their journey, to be picked up by services passing by at later periods.

2.2 RM Strategy

Revenue Management groupes together a set of concepts and techniques aimed to better integrate customer behavior knowledge into the optimal capacity allocation models. For instance, different fares are applied to well differentiated products/services and different market segments are identified and used with the overall objective to maximise expected revenue. To define RM strategies for barge transportation systems, we introduce *customer classification* and *price differentiation*.

Customers are classified into three categories according to the business relationship: regular customers (R), who sign long-term contracts with the carrier or whom the carrier trusts; partially-spot customers (P), who contact the carrier infrequently and do not require that all their demand be accepted; fully-spot customers (F), who also require service irregularly but their demand must be accepted as a whole or not at all.

Let $\tilde{k}$ be the current booking request. Let $D(\tilde{k})$ be the set of demands accepted before the arrival of $\tilde{k}$, and $K(\tilde{k})$ the set of forecasted future demands with direct interactions in time with $\tilde{k}$. A transport request $\tilde{d} \in D(\tilde{k}) \cup K(\tilde{k}) \cup \tilde{k}$ is then characterized by the volume to be transported in TEUs, $vol(\tilde{d})$; the origin and destination terminals, $o(\tilde{d})$ and $d(\tilde{d})$, respectively; the time $t_{res}(\tilde{d})$ it is submitted to the booking system; the time $t_{avl}(\tilde{d})$ it becomes available at its origin terminal and the corresponding anticipation time, $\Theta(\tilde{d}) = t_{avl}(\tilde{d}) - t_{res}(\tilde{d})$; the due time (latest delivery time) $t_{out}(\tilde{d})$ and the requested delivery time $\Delta(\tilde{d}) = t_{out}(\tilde{d}) - t_{avl}(\tilde{d})$; the unit tariff $f(\tilde{d})$ according to the fare class of the demand (defined bellow); and the category $cat(\tilde{d})$ of customers (R, P or F). Note that a future demand k is considered to be part of the set of potential future demands $K(\tilde{k})$ when it has "direct interactions" with the current booking request $\tilde{k}$, which is true when the two time conditions are satisfied:

- $t_{res}(k) > t_{res}(\tilde{k})$
- $[t_{avl}(k), t_{out}(k)] \cap [t_{avl}(\tilde{k}), t_{out}(\tilde{k})] \neq \emptyset$.

Let $VMAX(k)$ be the maximum volume a future demand request $k \in K(\tilde{k})$ may take, and $P_k(x)$ the discrete probability distribution function indicating the probability that a given value $0 \leq x \leq VMAX(k)$ occurs.

We define four fare classes for any pair of terminals in the physical network (and the distance separating them) as the combination of $\Theta(\tilde{d})$, early or late booking, and $\Delta(\tilde{d})$, slow or fast delivery requested. A demand with the highest fare class thus corresponds to a late booking and fast delivery request, while a demand with the lowest fare class corresponds to an early booking and slow delivery request.

The proposed RM strategy for barge transportation is then to examine each new transport request, $\tilde{k}$, and decide on its acceptance, and routing through the network for accepted ones, by considering its *feasibility* and *profitability*, given the current status of the network and an estimation of future demands. The former means that currently there is sufficient capacity and time to satisfy $\tilde{k}$. The latter indicates that the expected total revenue given the acceptance of $\tilde{k}$ is at least not worse than the one corresponding to rejecting it, taking into account the potential future demands. The model of Section 3 is used to make these decisions.

A rejected request has no influence on the transport network. Similarly, the potential future demands are only used to calculate the expected total revenue, and do not impact the status of the network.

3 The Formulation

We now present the Revenue Management decision model that is to be solved for every arriving request for transportation $\tilde{k}$. The decision variables are:

- $\xi(\tilde{k})$: accept or reject $\tilde{k}$, where $\xi(\tilde{k})$
  - equals 1 when $cat(\tilde{k})$ = R,
  - varies within [0, 1] when $cat(\tilde{k})$ = P,
  - takes the value 0 or 1 when $cat(\tilde{k})$ = F;
- $v(\tilde{k}, a)$: volume of demand $\tilde{k}$ on arc a;
- $maxvol(k)$: maximum volume available on the network (at the decision time) to serve the potential future demand $k \in K(\tilde{k})$;
- $v(k, a)$: volume of the potential future demand $k \in K(\tilde{k})$ on arc a.

Obviously, $\xi(d)$ and $v(d, a)$ variables are fixed on all arcs for the already accepted demands, which we denote d, $d \in D(\tilde{k})$.

The objective function of the model with respect to the current demand $\tilde{k}$ maximizes the sum of its corresponding revenue and the expected revenue computed on the basis of future demand forecasts:

$$\max\ (f(\tilde{k}) \cdot \xi(\tilde{k}) \cdot vol(\tilde{k}) + \phi) \tag{1}$$

where

$$\phi = \sum_{k \in K(\tilde{k})} f(k) \sum_{x=0}^{maxvol(k)} x P_k(x) \tag{2}$$

Following [2], ϕ is linearized by introducing additional binary decision variables y_{kj} for each potential future demand k, where the integer-valued j takes all the values between 1 and $VMAX(k)$. Note that $VMAX(k)$ represents the maximum possible volume of a booking request, which translates mathematically, in terms of probability distribution, as $P_k(j) = 0$ when $j \geq VMAX(k) + 1$. The binary decision variables y_{kj} are defined to be equal to 1, if no more than volume j of capacity is available on the network to serve the potential future demand k and 0 otherwise. In order to make this definition consistent, for each future demand k, at most one of the variables y_{kj} may take the value 1 (since this will correspond to the maximum capacity available on the network to serve that specific demand). Thus, the objective function becomes:

$$\max\ (f(\tilde{k}) \cdot \xi(\tilde{k}) \cdot vol(\tilde{k}) + \sum_{k \in K(\tilde{k})} f(k) \sum_{1 \leq j \leq VMAX(k)} y_{kj} \sum_{x=0}^{j} (x P_k(x))) \tag{3}$$

since $maxvol(k)$ is defined as follows:

$$maxvol(k) = \sum_{1 \le j \le VMAX(k)} j y_{kj} \tag{4}$$

with

$$\sum_{1 \le j \le VMAX(k)} y_{kj} \le 1 \tag{5}$$

and

$$y_{kj} \in \{0, 1\}. \tag{6}$$

Following this definition, note that the optimal value of $maxvol(k)$ is computed (4) as a result of the optimisation problem. Thus, this optimal value is obtained when maximizing the expected revenue corresponding to current demand $\tilde{k}$ on the network, taking into account the entire remaining available capacity and the overall profitability of the whole set of potential future demands on that specific time window.

The constraints of the model are the usual flow conservation relations at nodes and the capacity restrictions imposed by the service network. The latter take the form defined by (7) for each service leg

$$\sum_{k \in K(\tilde{k})} v(k, a) + v(\tilde{k}, a) \le cap\_avl(a), \quad \forall a \in A_L \tag{7}$$

while the flow conservation constraints for all nodes $n(i, t) \in N_{IT}$ are:

$$\sum_{a \in A^+(n(i,t))} v(\tilde{k}, a) - \sum_{a \in A^-(n(i,t))} v(\tilde{k}, a) = \begin{cases} \xi(\tilde{k}) vol(\tilde{k}) & \text{if } (i, t) = o(\tilde{k}) \\ 0 & \text{if } (i, t) \ne o(\tilde{k}),\ (i, t) \ne d(\tilde{k}) \\ -\xi(\tilde{k}) vol(\tilde{k}) & \text{if } (i, t) = d(\tilde{k}) \end{cases} \tag{8}$$

and

$$\sum_{a \in A^+(n(i,t))} v(k, a) - \sum_{a \in A^-(n(i,t))} v(k, a) = \begin{cases} maxvol(k) & \text{if } (i, t) = o(k) \\ 0 & \text{if } (i, t) \ne o(k),\ (i, t) \ne d(k) \\ -maxvol(k) & \text{if } (i, t) = d(k) \end{cases} \tag{9}$$

where $A^+(n(i, t))$ and $A^-(n(i, t))$ stand for the sets of incoming and outgoing arcs, respectively, of node $n(i, t) \in N_{IT}$.

Finally, the constraints defining the range of the decision variables are:

$$\xi(\tilde{k}) = \begin{cases} 1, & \text{if } cat(\tilde{k}) = R \\ [0, 1], & \text{if } cat(\tilde{k}) = P \\ \{0, 1\}, & \text{if } cat(\tilde{k}) = F \end{cases} \tag{10}$$

$$v(\tilde{k}, a) \ge 0, \quad \forall a \in A \tag{11}$$

$$v(k, a) \ge 0, \quad \forall k \in K(\tilde{k}),\ \forall a \in A. \tag{12}$$

4 Simulation, Numerical Results and Analysis

To validate the proposed RM model, we use computer simulation. We simulate the sequential arrival of current demands as an iterative process. For each randomly generated demand, we run and solve the optimization problem and use the optimal decision to accept/reject the demand to update accordingly the status of the network in terms of remaining available capacity. Then, a new iteration is performed. The demand forecasts are considered to be known and given at the beginning of the simulation process. Several scenarios are used to test and validate the proposed model. We first set up a scenario with scarce resources and a very limited number of origin-destination (OD) pairs of transport requests. By using this scenario, we analyse the impact of different price ratios applied when different fares are introduced, corresponding to different classes of booking and delivery delays required by the customers. A second scenario, with a more comprehensive problem setting in terms of number of services, number of possible OD pairs of demands is devised. This second scenario is settled to discuss the performance of the RM model with respect to different levels of transportation capacity on the network, as well as with respect to the accuracy of demand forecasts. Based on the second scenario, possible strategies of negotiation when a demand is rejected are equally considered and numerical results analyzed. The remaining of this section is organised as follows. We briefly introduce the scenarios setting for the simulation in 4.1. We then illustrate and analyze the numerical results in 4.2.

4.1 Scenarios Setting

For all scenarios, four consecutive terminals, i.e., A, B, C and D, are considered to be located along the inland waterway with travel times for barges between any two consecutive terminals assumed to be the same. As for the service travel times, all the scheduled stops of a service (including at its origin and destination), are assumed to have identical durations as well, these delays corresponding to the time consumption for operations at port (e.g., loading/unloading containers). The maximum capacity of services is identical within one set of experiments but is varied from one scenario to another. The residual capacities of service legs are sequentially updated according to the accepted demands and their optimal routing. Holding arcs of containers at terminals have unlimited capacity.

Let us recall that any current demand $\tilde{k}$ is characterized by its $t_{res}(\tilde{k})$, $vol(\tilde{k})$, $o(\tilde{k})$, $d(\tilde{k})$, $t_{avl}(\tilde{k})$, $t_{out}(\tilde{k})$, $f(\tilde{k})$ and $cat(\tilde{k})$. We discretize the time so that no more than one reservation request ($t_{res}(\tilde{k})$) may arrive at each time instant during the simulation; $vol(\tilde{k})$ is a discrete random value between 0 and VMAX (the same maximum volume is assumed for any demand) following a given probability distribution function; $vol(\tilde{k}) = 0$ indicates that there is no booking request for the current time instant. The origin-destination pair, thus the values of $o(\tilde{k})$ and $d(\tilde{k})$, are uniformly generated out of the set of possible OD corresponding to a scenario. Both anticipation $\Theta(\tilde{k})$ and delivery time $\Delta(\tilde{k})$ are randomly selected from a predefined pool of possible values, following the uniform distribution; the generation of the latter is equally related to the distance between the $o(\tilde{k})$ and the $d(\tilde{k})$ of the demand. The $t_{avl}(\tilde{k})$ and $t_{out}(\tilde{k})$ are then computed accordingly. Thresholds for the anticipation and delivery time are predefined to split the demands into early/late reservation and slow/fast delivery types, respectively. For a given distance of an OD, a basic fare p is predefined. The unit transportation price (per container) is then defined as $f(\tilde{k}) = p \cdot r_\Theta \cdot r_\Delta$, where r_Θ and r_Δ are the anticipation ratio and the delivery ratio respectively. Their corresponding values for early reservation and slow delivery are both set to 1, the others being integer values (factors) greater than one, corresponding to larger fares charged on high contribution demands requesting higher quality-of-service transportation. Finally, $cat(\tilde{k})$ is randomly generated among R, P and F following the uniform distribution.

For each current demand $\tilde{k}$, the corresponding set of potential future demands is generated following the same generation procedure, except for its volume. Indeed, since the objective function is defined based on the mathematical expectation of the potential revenue of future demands, this computation is performed considering all the possible volumes (from 0 to VMAX), weighted by their probabilities. The summation is bounded, however, by the maximum available capacity (at decision time) on the network to satisfy each specific future demand k ($maxvol(k)$). Following the same idea, note that the categories (i.e., R, P or F) of future demands are not needed either when generating the potential future demands. By doing so, an estimated value of the expected revenue is obtained by simulation and used to make the decision of accepting or rejecting the current demand $\tilde{k}$.

For all the scenarios in the simulation, a FCFS accept/reject policy is conducted as comparison. No potential future demands are considered for the FCFS model. A current demand $\tilde{k}$ is accepted when at least one feasible route exists in the space-time network, without considering the expected revenue and hence, without considering its profitability.

The characteristics of the first scenario are:

- Length of the simulated time horizon is 300 time instants;
- There are 15 identical services defined, starting every 20 time instants, from A to D with an intermediate stop at B;
- 3 different ODs are considered: AB, BD and AD;
- Different experiments are conducted, with different values of the anticipation ratio (r_Θ) for late reservation and the values of the delivery ratio (r_Δ) for fast delivery: 1, 2, 3 and 4.

The characteristics of the second scenario are:

- Length of the simulated time horizon is 600 time instants;
- There is a total of 30 services running on the network, 15 in each direction: from A to D and from D to A; they all stop at all terminals;
- All 12 possible ODs are considered;
- Different experiments are conducted, with different capacities of services : 5, 10 and 20 (TEUs);
- Different experiments are conducted, based on different forecast accuracies: good accuracy, underestimation, overestimation.

4.2 Numerical Results and Analysis

The results obtained when running experiments on the first scenario are illustrated in Fig. 1. Fig. 1 (a) presents the ratio between the total revenue obtained with the RM model and the total revenue obtained with the FCFS policy, corresponding to different price ratios. Fig. 1 (b) presents the corresponding ratios of the number of nonprofitable rejected requests over the total number of rejected requests when applying the RM model. On the horizontal axis, r indicates the value of the anticipation ratio (r_Θ) for late reservation and the value of the delivery ratio (r_Δ) for fast delivery; they are considered to have both the same value r. As expected, better revenue is always obtained by applying the RM model when compared with the FCFS policy. When we increase the price ratio r, the difference in profitability of low-fare compared to high-fare demands grows as well. A low-fare demand, which has a feasible routing in the transport network, has then a higher chance to be less profitable compared to a potential future high-fare demand (even if its probability to occur is low) and consequently will be rejected or not fully accepted. Therefore, as shown in Fig. 1 (b), when we increase the price ratio r, more demands are rejected because of this economic discrimination (nonprofitability). Consequently, a boost in revenue, as illustrated in Fig. 1 (a) is obtained when we increase the anticipation and delivery price ratios.

Note that, even without any price differentiation, the RM model still generates better solutions in terms of total revenue (Fig. 1 (a), when r=1). In fact, the consideration of future demands equally aids in finding the best routing solution when a demand is accepted. This better routing makes room in the space-time network for potentially infeasible future demands, and hence convert them to feasible, which is transformed accordingly into extra revenue.

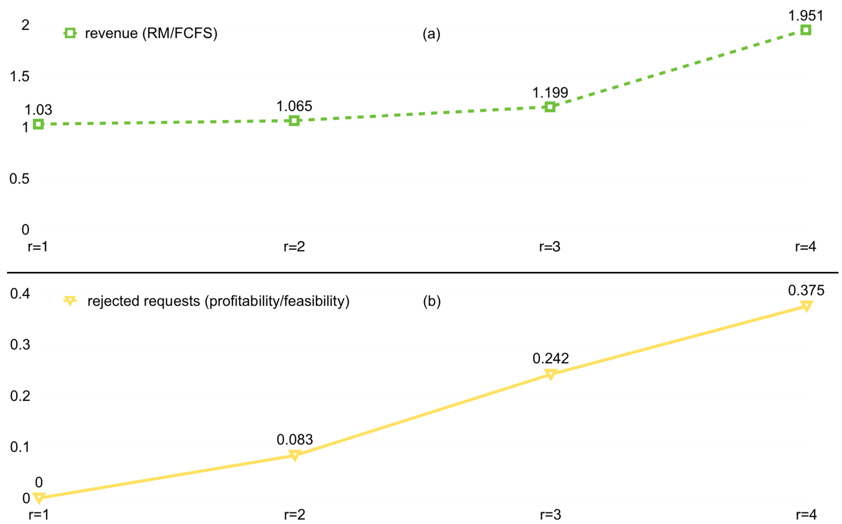

Figure 1: Effect of price differentiation on revenue (a) and on rejected requests (b)

Table 1: Total revenue of RM/FCFS

	Service Cap.=20	Service Cap.=10	Service Cap.=5
Real:Estimate=1.0	1.0483	1.0531	1.7196
Real:Estimate=1.5	1.0093	1.0391	1.0655
Real:Estimate=0.5	1	1.0093	1.0282

The ratios between total revenues generated when applying the RM model and when applying the FCFS policy within the second scenario are presented in Table 1. To examine the sensitivity of the RM model to bad forecast accuracy situations, we conduct three different simulations related to the accuracy of the demand forecasts, in terms of volume. In these simulations, if the arrival process of demands to the booking system follows the same probability distribution function as considered in the objective function of the RM model, we say the demand forecast is accurate (Real:Estimate=1.0). Real:Estimate=1.5 indicates the demands are underestimated by a factor of 0.67, while Real:Estimate=0.5 indicates that the demands are overestimated by a factor of 2. The behavior of the RM model with respect to different levels of maximum service capacity is also studied. The values 20, 10 and 5 TEUs for the maximum service capacities are used in three independent sets of experiments.

As expected, the RM model generates higher total revenue than FCFS when the demand forecast is accurate. However, even when demands are not coming as expected, RM model still defeats its competitor. The only exception happens in the simulation when the demands are overestimated and the service capacity is relatively high: the two models generate the same total revenue. The good performance of the RM model is found

Table 2: Number of rejected demands of RM/FCFS

	Service Cap.=20	Service Cap.=10	Service Cap.=5
Real:Estimate=0.5	1/1	14/16	59/60
Real:Estimate=1.0	17/25	76/82	143/151
Real:Estimate=1.5	70/74	207/220	266/280

to overcome the influence of underestimation which implies more booking requests than expected, which can be relatively interpreted as a scarce resource situation. Another observation from Table 1 is that the less network capacity we have, the better the RM model responds. Therefore, the best revenue ratio (1.7196) is obtained when the resource is scarce and the demand forecast is accurate.

The reason why the RM model generates better solutions can be as follows: fully or partially denying demands (due to the different customer categories) create the possibility of saving the precious resource for more profitable (due to higher contribution fares) future demands; to accept a demand, the best routing is decided by taking into account the potential future demands. Consequently, the better routing of current demand may convert some of the potentially infeasible future demands into feasible demands.

Due to the introduction of RM techniques, less demands are rejected compared with FCFS. As shown in Table 2, the number of rejected demands when applying the RM model, is always less than the corresponding number of rejected demands with the FCFS policy. Given the same level of accuracy of demand forecast, less demands are rejected with higher network capacity. However, the difference between the two competitors is slight. For the RM model, almost one third of the denied transport requests correspond to regular (R) customers.

Therefore, we design another set of simulations including a negotiation phase with the rejected R category customers. Three different strategies, Nego_RM, Nego_FCFS and Nego_PP, are integrated with the proposed RM approach. Once a demand from an R customer is rejected, the negotiation phase is triggered. Both Nego_RM and Nego_FCFS strategies then consider that rejected R demand as a P demand. However, the former tries to fit this demand in the transport network considering estimated future demands (RM model), while the later tries to accept this demand on the transport network in a greedy manner (FCFS model). Instead of changing the category of the demand, the Nego_PP strategy still treats an R customer as regular. In order to transport it, the delivery delay of this demand is extended and a lower unit price is charged (as penalty). For all the tests, a FCFS policy is also carried on as comparison. The effect of different negotiation strategies for rejected R type demands on the total revenue and the percentage of successful negotiation is illustrated in Table 3.

In Table 3, Price Ratio indicates the tested values of both r_Θ late reservation and

Table 3: Effect of different negotiation strategies for rejected R customers

Price Ratio	Nego. Strategies	Revenue/FCFS	Successful Nego. (%)
r=2	RM	1.1477	0
	Nego_RM	1.1868	15.25
	Nego_ FCFS	1.1849	16.67
	Nego_PP	1.0543	53.52
r=3	RM	1.1493	0
	Nego_RM	1.6227	16.39
	Nego_ FCFS	1.5365	31.88
	Nego_PP	1.2772	54.29
r=3	RM	1.7394	0
	Nego_RM	1.7533	11.11
	Nego_ FCFS	1.7436	16.67
	Nego_PP	1.3500	53.13

r_Δ fast delivery. Revenue/FCFS indicates the ratio of total revenue obtained by RM model with (or without) negotiation phase related to FCFS, and Successful Nego shows the percentage of successful negotiation corresponding to each strategy. Even combined with negotiation, RM model still generates better solutions than FCFS. For a given price ratio, Nego_RM always generates slightly better solutions, in terms of total revenue, compared with Nego_FCFS. On the other hand, the latter always has better performance in negotiation than the former. Therefore, carriers can choose the appropriate strategies according to the requirements of their regular customers. In case that R customers have a relative loose constraint on the delivery time, Nego_PP succeeds more than 50% in the negotiation process for all tested price ratios. One may argue that there exists other possible ways to compensate; we do not claim the proposed negotiation strategies are the best solutions. Instead, we put the emphasis on the fact that with the proposed RM approach, we offer to the carriers a panel of possible ways to simultaneously increase the satisfaction of regular customers and make more revenue. Different negotiation strategies may be adopted based on different types of behavior characterizing regular customers.

5 Conclusions

In this paper, we present a Revenue Management (RM) approach for dynamic capacity allocation of the intermodal barge transportation network. A new model is proposed considering the RM strategies. According to the business relationship, customers are classified into three categories, whose transport requests are accordingly treated differently. A price policy, related to the booking anticipation and delivery type, is also applied to differentiate the products. We conduct a set of experiments to validate the RM approach. Compared with the first-come first-serve (FCFS) based booking strategy, the RM model always generates better total revenue, even with inaccurate demand forecast. Another observation is that facing scarce resource (small transport capacity), the RM model easily outscores its competitor, and this trend grows when resource levels decrease. We also discuss a set of possible negotiation strategies combined with the proposed RM model and conclude that with slightly lower total revenue the decision support still offers the possibility to better satisfy loyal (regular) customers and generate more revenue compared with FCFS. Encouraged by these preliminary results, we are considering to study how the penalty or compensation for the denied regular demands should be further integrated into the new RM model proposed.

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