Incorporating competitive price information into revenue management

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ABSTRACT
KEYWORDS: revenue management, competition

In a marketplace with many service providers offering the same or similar products, demand is largely driven by competition. This competitive aspect, however, is not considered explicitly in most existing revenue management (RM) approaches. This paper introduces a new approach that uses a recently developed demand model and competitive price information. A simulation study was conducted to compare the performance of this new approach and several other approaches. Our results lead to several observations and insights into the performance of different approaches and show that incorporating competitive data into RM is a promising direction.
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INTRODUCTION

Competition is often the most significant demand driver nowadays in a marketplace with many service providers offering the same or similar products. With the rapid development of the internet, customers can compare prices of different service providers at a mouse click. A significant portion of customers make a purchase from the provider that offers the lowest price. This type of purchase behaviour is confirmed by many revenue management (RM) analysts in the service industry.

Most demand models that are used in existing RM systems do not explicitly consider price-driven demand in the presence of competition. Two types of demand models are widely used: yieldable demand and priceable demand. Traditionally, customers are assumed to belong to different ‘classes’ where customers from each class only requests a specific product. We say such demand is yieldable. Models based on yieldable demand models form the basis of what is currently used in many RM systems. Another type of demand model assumes that customers have different willingness-to-pay

(WTP). A customer purchases at the lowest price available that is below his WTP. A customer is lost when the lowest price available is higher than the WTP of that customer. We call such demand priceable demand. See Boyd and Kallesen (2004) for a more detailed discussion of yieldable and priceable demand models. In yieldable and priceable demand models, customer demand is assumed to be provider specific; that is, a customer either buys from the provider or is lost.

Yieldable and priceable demand models do not explicitly model demand under competition. In Salch *et al.* (2004), a market priceable demand model is introduced. In this demand model, a customer is assumed to purchase at the lowest price available in the market regardless of the service provider as long as that price is lower than the customer's WTP. While the market priceable demand model cannot model complex customer choice behaviour, it captures the demand that is largely driven by prices in a competitive situation.

This paper studies the performance of several RM approaches in a purely market priceable demand environment. In addition to EMSRb (Belobaba, 1992) and Hybrid Dynamic Program (HDP) (Oosten and Walczak, 2005), we propose a new methodology called the Modulated Dynamic Program (MDP). HDP considers both yieldable and priceable demand. MDP uses market priceable demand forecast and competitive price information. While one can easily think of competitive information that can be useful in a competitive environment, the availability of such information is often an issue in practice. We assume the availability of competitive price information, which is often publicly available. We would like to point out that an approach that uses more competitive information, for example, competitors' real-time inventory, can potentially yield more revenue gains.

We strive to answer the following questions in this research.

1. What is an appropriate approach that uses competitive information?
2. How is the performance of approaches that do not consider competition explicitly?
3. How is the performance of some simple approaches that use competitive information, for example, price matching?

We use both analytical and simulation tools to study these issues. Our numerical experiments and analysis lead to useful observations and insights into the performance of the different approaches.

This paper is organised as follows: the following section gives a brief review of the literature. Next, we introduce the MDP model. Then, we report and analyse results from our simulation study and finally conclude with a summary of results.

BRIEF REVIEW OF LITERATURE

Price competition has been an area of intensive study in economics. Chapter 8 of Talluri and van Ryzin (2004) gives a brief overview of that literature relating to RM concepts. Indeed, many stylised models of RM techniques (pricing, resource allocation, etc) under competition are studied in this stream of literature. Much of the focus is on the effectiveness of these techniques under different competitive situations and insights thereof.

In recent years, competition has been the topic of a growing body of research in RM literature. Game theoretical models are used in much of this research to study interactions among multiple competitors when each is following a specific type of RM strategy. Netessine and Shumsky (2005) study the competition and coordination issues in a static game that involves two airlines. Gallego and Hu (2006) study a differential game that is modelled as a stochastic control problem in continuous time. It is assumed in both papers that each competitor has full information (or sufficient information to derive all information of interest) about their competitors, including capacity, demand, and control strategies.

This paper has a different focus. We do not study the problem from a game-theoretical

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perspective. Rather, we are interested in the performance of various strategies used by the service providers. The MDP model that we propose in the paper uses only competitive price information. Other information such as policy and capacity about the competitor is not included in this model. We conduct numerical experiments to study the effectiveness of such an approach and contrast it with that of several other widely used approaches in practice. Analysis of our simulation experiments yields useful insights on the performance of each approach.

In our demand model, we assume that customers will purchase the product with the lowest prices and demonstrate no provider preference. In such an environment, the demand seen by one competitor is dependent on the price level chosen by his competitor. Since a Markov chain model is used to model the price level of the competition, the demand process is modulated by a Markov chain. Such a demand model was studied intensively in the inventory literature; see, for example, Chen and Song (2001).

THE MDP

Even if all competitive information is available, the sheer volume of information would make it difficult to incorporate it all into forecasting and optimisation. For example, to fully capture the impact of the competitors' inventory, real-time inventory information of competitors, if available, needs to be considered in the optimisation approach.

Other than inventory information, other information about competitors is also very useful, including inventory control mechanism, future price initiatives, and current price. This type of information is usually not publicly available, with the exception of the prices that are being charged. In this section, we utilise a dynamic program that considers market priceable demand and makes use of information on the prices charged by the competitor. In particular, two types of pricing information are used: the current competition price and the transition of the competition price. The transition matrix of prices is denoted by $A=[a_{ij}]$, where a_{ij} is the probability that the competitor offers price tier j in the next period, given that he offers price tier i in the current time period. The dummy index 0 is used when the competitor does not accept bookings. Figure 1 shows the price transition matrix for a three-class example with prices \$350, \$250, and \$150.

The price transition matrix in our simulation study is obtained from simulation statistics. In practice, such information can be obtained by monitoring competitive price levels. In the service industry, many airlines have already invested in doing this, even though an implementation of our approach may require a more systematic approach for doing so.

There are two competing firms in the market offering similar products. The competitors are denoted competitor 1 and competitor 2. We study the problem from competitor 1's perspective. We assume that both competitors offer n price tiers and the price points used are the same. The price for tier k is r_k. We assume that the prices are ordered such that $r_1>r_2>\cdots>r_n$. The set of price points is denoted $P=\{r_0,r_1,\ldots,r_n\}$, where r_0 is a null price that shuts off all demand.

Price this period	Price next period: Closed	\$350	\$250	\$150
Closed	1	0	0	0
\$350	0.052	0.851	0.097	0
\$250	0	0.011	0.904	0.085
\$150	0	0	0.373	0.627

Figure 1: Price transition matrix for a three-class example with prices \$350, \$250, and \$150

We consider a discrete-time formulation with T time periods. Time is indexed forward so that a smaller time index refers to an earlier time period. We assume that all demand is market priceable. Let λ_{tk} be the arrival probability of a customer in period t, given that the lowest price offered by the two competitors is r_k. In a given period, we use a vector $p=(p^1,p^2)$ to denote the prices offered by the two competitors. Since demand is market priceable, if $p^1>p^2$, all customers go to competitor 2; if $p^1<p^2$, all customers go to competitor 1. When $p^1=p^2$, we assume that half of the demand goes to each competitor. Note that this assumption can be easily relaxed so that customers may demonstrate provider preference when the prices offered are the same. Since in a market priceable environment, the demand seen by competitor 1 is affected ('modulated') by the price offered by competitor 2, we call this dynamic program the MDP.

The state is denoted (x,i), where x is the remaining inventory and i is the tier index of the price offered by competitor 2. Let $v_t(x,i)$ denote the maximum revenue obtained from period t onward given state (x,i). The optimality equations of the dynamic program are

$$\begin{aligned}
v_t(x,i) = \max\Bigg\{ & \sum_{j=0}^{n} a_{ij} v_{t+1}(x,i), \\
& 0.5\lambda_{ti}\left[r_i + \sum_{j=0}^{n} a_{ij} v_{t+1}(x-1,i)\right] \\
& \quad + (1-0.5\lambda_{ti}) \sum_{j=0}^{n} a_{ij} v_{t+1}(x,i), \\
& \max_{k>i} \Bigg\{ \lambda_{tk}\left[r_k + \sum_{j=0}^{n} a_{ij} v_{t+1}(x-1,i)\right] \\
& \quad + (1-\lambda_{tk}) \sum_{j=0}^{n} a_{ij} v_{t+1}(x,i)\Bigg\}\Bigg\} \quad \forall t,x,i
\end{aligned} \tag{1}$$

The boundary conditions are

$$v_{T+1}(x,i) = 0 \ \forall x,i \tag{2}$$

The three terms within maximisation in (1) corresponds to pricing high, matching, or pricing lower. We use the standard backward induction algorithm to solve the model.

SIMULATION STUDY

We use simulations to compare the performance of several different RM methodologies in a purely market priceable demand environment. There are two competitors, each with a capacity of 100. There are six price tiers, with prices \$700, \$600, \$500, \$400, \$300, and \$200. The demand means are 10, 10, 20, 40, 40, and 80. We consider three demand scenarios. In the medium-demand case, the demand means are used. In the high-demand case, the demand means are inflated by a factor of 1.25. In the low-demand case, the demand means are deflated by a factor 0.75. Note that the demand to capacity ratio, defined by the total mean demand divided by the total capacity, is 1.25, 1, and 0.75 for the high-, medium-, and low-demand scenarios. There are five data collection points (DCP) at the beginning of five equal-length time intervals.

Table 1 lists the solution methodologies used in our simulation study. EMSRb is re-solved for each DCP taking into account the remaining capacity and unrealised demand up to the re-solving point. Bid-price controls are used for HDP and MDP. A single bid-price vector is used for each DCP, where the ith element represents the bid-price of the ith unit of capacity. The bid-price values are averages over all bid-price values for each time unit within the relevant DCP in a discrete-time dynamic programming implementation.

Simulation results and analysis using EMSRb/EMSRb as a baseline

Table 2 shows the average revenues with corresponding half-widths of 95 per cent confidence intervals over 500 simulation runs and relative performance when EMSRb/EMSRb revenues are used as the baseline. In EMSRb/EMSRb, both competitors use EMSRb as described in Table 1. Similarly, in EMSRb/

Table 1: Solution methodologies considered in the simulation study

Method	*Forecaster*	*Optimiser*
EMSRb	Yieldable	EMSRb
HDP	Yieldable and priceable	Hybrid dynamic program that considers both yieldable and priceable demand
MDP	Market priceable	Modulated dynamic program
Matching	Yieldable	Match the competitor's price whenever possible; when the competitor is out of inventory, use controls from EMSRb

HDP, competitor 1 uses EMSRb and competitor 2 uses HDP.

We first discuss the results for EMSRb/HDP. For the high-demand scenario, both competitors show significant revenue lift from EMSRb/EMSRb. Competitor 2, who uses HDP, performs better than competitor 1, who uses EMSRb. The competitors also show revenue lift for the medium-demand case; however, the magnitude of improvement over EMSRb/EMSRb is much smaller than that of the high-demand case. The performance of EMSRb/HDP in the low-demand case is very close to EMSRb/EMSRb.

The revenues for EMSRb/Matching are very close to EMSRb/EMSRb revenues in all demand scenarios. This should not be surprising since the competitors are identical in capacity and demand. This does suggest that price matching, although fairly popular in practice, may not lead to desirable revenue lift. Another motivation for using price matching is often to 'penalise' competitors who use prices that are perceived as too low. The results indicate that price matching cannot achieve this objective as well. In fact, the revenue of competitor 1 whose prices are matched does not show significant revenue drop.

Table 2: Mean revenues with corresponding half-widths for 95 per cent confidence intervals over 500 simulation runs and percentage revenue differences from EMSRb/EMSRb revenues

	EMSRb/EMSRb		*EMSRb/HDP*		*EMSRb/Matching*		*EMSRb/MDP*	
High	(19,995, 131)	(19,919, 139)	(22,296, 72)	(22,717, 516)	(20,006, 138)	(19,912, 138)	(19,951, 132)	(21,748, 233)
Medium	(18,403, 217)	(18,447, 215)	(18,740, 210)	(19,227, 326)	(18,381, 216)	(18,469, 214)	(18,392, 214)	(18,639, 229)
Low	(14,848, 270)	(14,929, 268)	(14,905, 273)	(14,900, 268)	(14,851, 270)	(14,926, 267)	(14,845, 270)	(14,932, 267)
High	—	—	11.51%	14.05%	0.06%	−0.04%	−0.22%	9.18%
Medium	—	—	1.83%	4.23%	−0.12%	0.12%	−0.06%	1.04%
Low	—	—	0.38%	−0.19%	0.02%	−0.02%	−0.02%	0.02%

In EMSRb/MDP, the revenue performance of competitor 1 using EMSRb is again close to the baseline. Competitor 2, who uses MDP, however, shows significant revenue lift for the high-demand case and moderate revenue lift for the medium-demand case. The magnitude of revenue lift for competitor 2, however, is smaller than the EMSRb/HDP case.

To gain more insight into the simulation results, we looked at the inventory and price trajectories in the simulation runs. We will focus on high-demand scenarios, where we see the most diverse and interesting results. Figure 2 shows the inventory and price trajectories for EMSRb/EMSRb in the high-demand case. We choose to show them for selected runs (the 100th, 200th, 300th, and 400th run). In all runs, the inventory was depleted before the end of the sales horizon for both competitors. Also, the $200 price was used most of the time until a short time before the inventory was sold out where the price is raised to $300 briefly. This suggests that the controls from EMSRb lead to prices that are too low.

Figure 3 shows the inventory and price trajectories for EMSRb/HDP. As in the EMSRb/EMSRb case, competitor 1 runs out of inventory well before the end of the sales horizon in all cases. The inventory for competitor 2, however, was not used up in all four runs that we looked at. At the beginning of each run, HDP charges a higher price than EMSRb for a period of time. Since all demand is market priceable, this means that competitor 2 will not see any booking during that time. After the inventory of competitor 1 is depleted, however, competitor 2 would enjoy a temporary monopoly in the market. This leads to a good explanation of the EMSRb/HDP results we see in Table 1. In particular, both EMSRb and HDP generate revenues that are much higher than the EMSRb/EMSRb case. Instead of competing on the low $200 price almost all the time as in the EMSRb/EMSRb case, both EMSRb and HDP enjoyed periods of monopoly. Hence, the aggressive nature of HDP benefited both competitors.

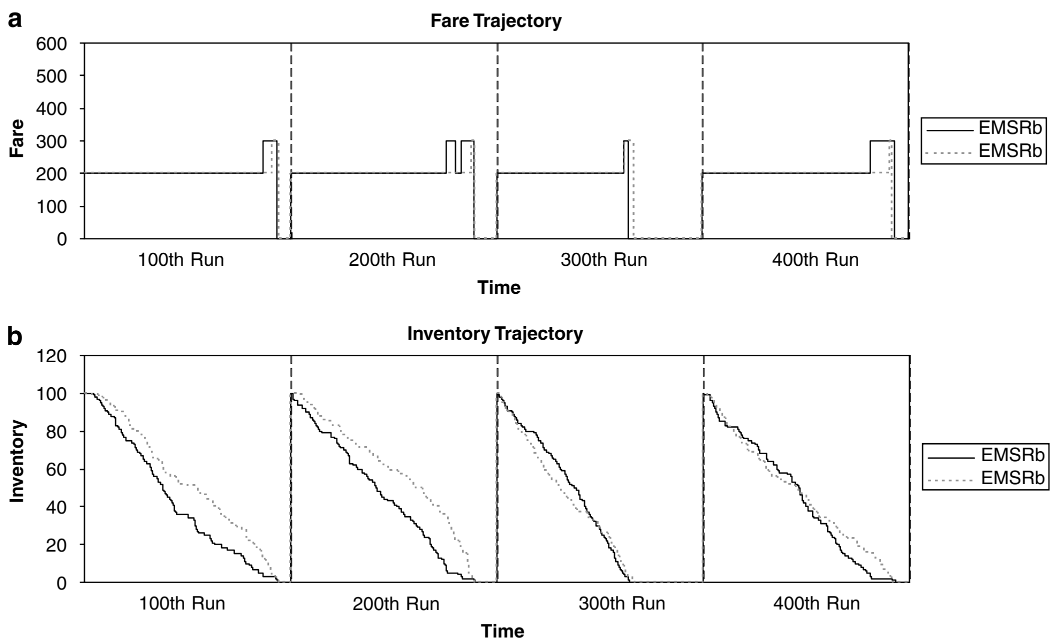

Figure 2: (a) Price trajectory for EMSRb/EMSRb in selected runs. (b) Inventory trajectory for EMSRb/EMSRb in selected runs

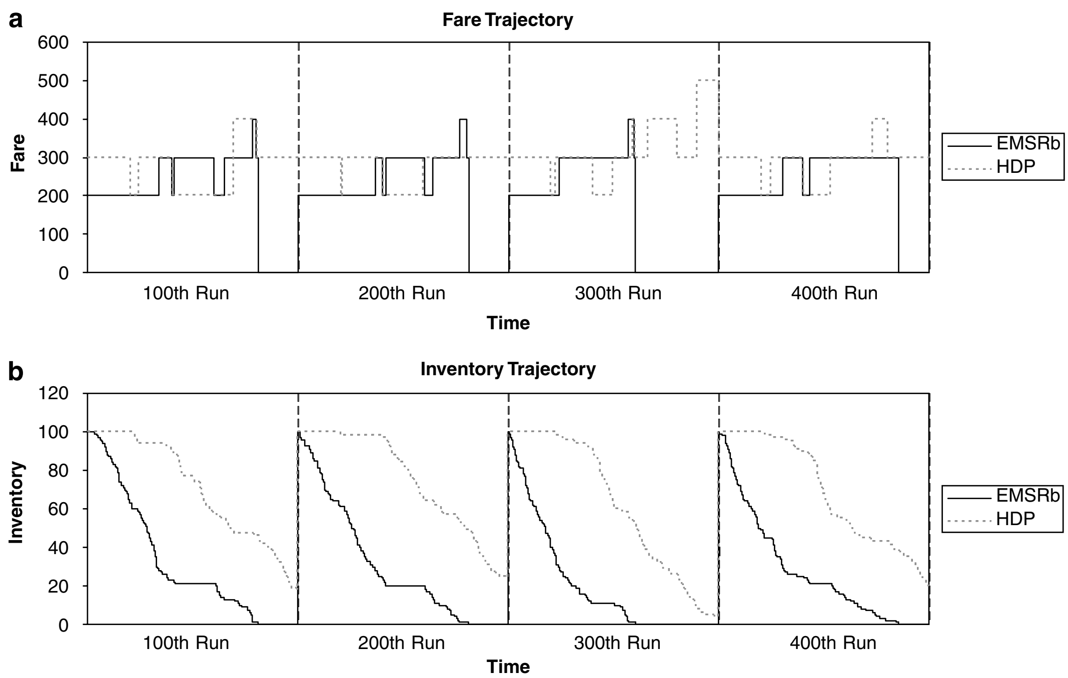

Figure 3: (a) Price trajectory for EMSRb/HDP in selected runs. (b) Inventory trajectory for EMSRb/HDP in selected runs

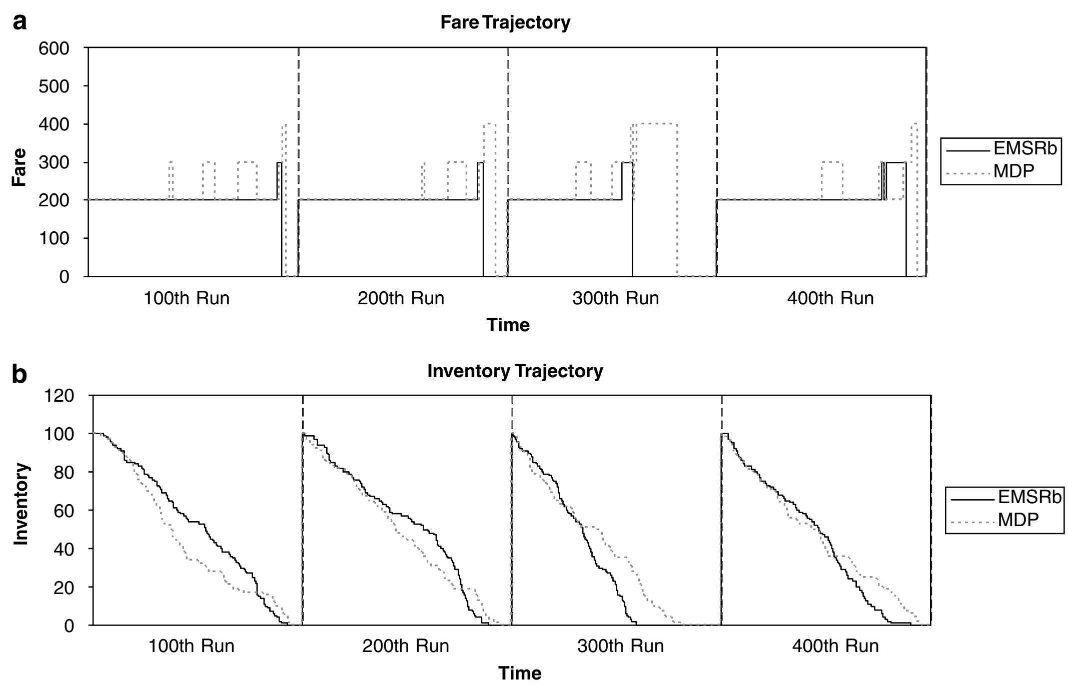

Figure 4: (a) Price trajectory for EMSRb/MDP in selected runs. (b) Inventory trajectory for EMSRb/MDP in selected runs

Figure 4 shows the price and inventory trajectories for EMSRb/MDP. The inventory of both competitors was depleted before departure for all runs. In three out of the four runs shown the inventory of MDP competitor was sold out near the end. The price trajectory suggests that the $200 price was used for both competitors most of the time; however, the MDP competitor occasionally raised his price to preserve inventory. It is also interesting to note that in all four runs right after the inventory of the EMSRb competitor is sold out, the MDP competitor raised his price. This should be contrasted to the HDP competitor in the EMSRb/HDP case.

In Figure 3, competitor 2 who uses HDP is not filled up in all four runs we showed in the graph. This motivated us to look at the resource utilisations in the simulation runs. Table 3 shows the average utilisations for the same runs as reported in Table 2. It should be pointed out that in EMSRb/HDP, the utilisation of HDP is significantly lower than all other utilisations reported in both high- and medium-demand cases. In particular, the utilisations for the HDP player are significantly lower than the utilisations of the MDP player in EMSRb/MDP. The MDP player, on the other hand, enjoyed utilisations that are very close to the utilisations of the EMSRb player in all runs. Therefore, even though HDP performs very well when in a head-to-head competition with an EMSRb player, the utilisations suffer significantly, which is often a cause of concern for some service providers. MDP does not have this shortcoming when in a head-to-head competition with EMSRb. It is also worth pointing out that the half-width of 95 per cent confidence intervals for MDP is significantly lower than that of HDP in both high- and medium-demand cases. This suggests that the MDP player enjoys a steadier stream of revenues across runs than the HDP player.

Simulation results and analysis using HDP/HDP as a baseline

Table 4 shows average revenues with corresponding half-widths over 500 simulation runs and the relative performance when HDP/HDP revenues are used as the baseline.

A comparison of HDP/HDP with EMSRb/EMSRb in Table 2 shows that HDP/HDP provides a much stronger baseline than EMSRb/EMSRb in terms of revenue. In fact, both EMSRb and Matching lead to lower revenue for competitor 2 when competitor 1 uses HDP. MDP, on the other hand, leads to a moderate revenue increase for competitor 2. The largest revenue increase is 2.43 per cent in the medium-demand case. HDP also suffers from a moderate revenue drop when in a head-to-head competition with MDP compared with the HDP/HDP case.

Figure 5 shows the price and inventory trajectories for HDP/MDP. In all four runs, the inventory of the HDP competitor was not completely depleted. The inventory of the MDP competitor was not completely depleted in three out of the four runs. The price trajectory shows that MDP usually had lower or equal prices than HDP. Given the leftover inventory in most of these runs, this strategy is reasonable since higher price leads to no bookings. It appears that MDP is able to take

Table 3: Average utilisations for simulation runs in Table 2

	EMSRb/EMSRb		*EMSRb/HDP*		*EMSRb/Matching*		*EMSRb/MDP*	
High	0.979	0.978	0.999	0.835	0.978	0.978	0.980	0.977
Medium	0.919	0.922	0.935	0.886	0.918	0.922	0.919	0.921
Low	0.742	0.746	0.745	0.743	0.743	0.746	0.742	0.747

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Table 4: Mean revenues with corresponding half-widths for 95 per cent confidence intervals over 500 simulation runs and percentage revenue differences from HDP/HDP revenues

	HDP/HDP		*HDP/EMSRb*		*HDP/Matching*		*HDP/MDP*	
High	(22,833, 341)	(22,924, 328)	(22,717, 516)	(22,296, 72)	(22,878, 365)	(22,515, 338)	(22,082, 398)	(23,009, 166)
Medium	(19,274, 279)	(18,997, 297)	(19,227, 326)	(18,740, 210)	(19,069, 314)	(18,909, 302)	(18,780, 324)	(19,458, 239)
Low	(14,825, 271)	(14,985, 269)	(14,900, 268)	(14,905, 273)	(14,880, 276)	(14,822, 261)	(14,799, 271)	(15,000, 271)
High	—	—	−0.51%	−2.74%	0.20%	−1.78%	−3.29%	0.37%
Medium	—	—	−0.24%	−1.35%	−1.06%	−0.46%	−2.56%	2.43%
Low	—	—	0.51%	−0.53%	0.37%	−1.09%	−0.18%	0.10%

advantage of the aggressiveness of HDP to gain additional revenue.

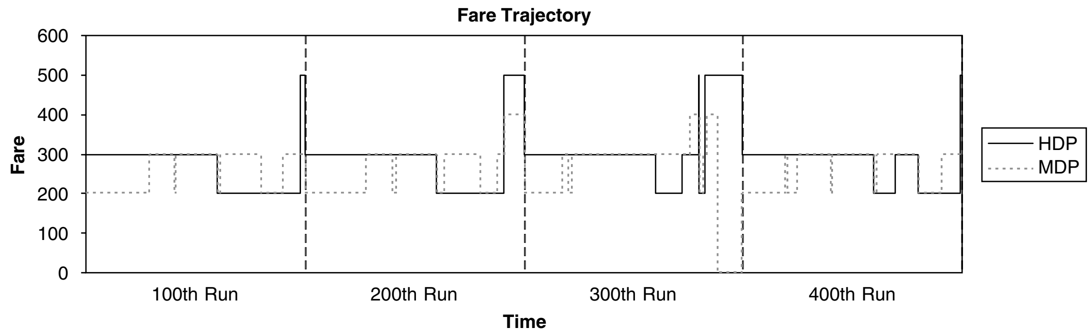
A further look at the utilisations leads to additional insights. Table 5 shows the average utilisations for runs reported in Table 4. HDP utilisations are significantly lower than those of EMSRb and MDP in all high- and medium-demand cases. Not surprisingly, the utilisations of competitor 2 are close to those of competitor 1 in HDP/Matching. Therefore, MDP is the only strategy that leads to higher revenues and higher utilisations simultaneously. This is a very appealing feature of the strategy.

SUMMARY

We introduce an RM approach that utilises competitive price information. In this approach, the competitive price level is modelled as a Markov chain. A dynamic programming model, MDP, is used to formulate and solve the problem. We conduct a simulation study that compares the performance of this approach to more traditional approaches that ignore competition. Our results indicate that this new approach performs very well when in a head-to-head competition with two existing approaches.

We formulated the MDP considering a purely market priceable demand environment. It is straightforward, however, to extend this approach to cases with yieldable and priceable demand. We used a market with two competitors to introduce our model. Since we only need to keep track of the lowest price available in the market, our approach is also applicable in a market with multiple competitors.

One of the key considerations for an approach that makes use of competitive data concerns the availability of such data. This paper assumes that competitive price information is available, which we believe is a fairly reasonable assumption. Additional data, if available, are likely to lead to an approach that will perform even better in a competitive environment.



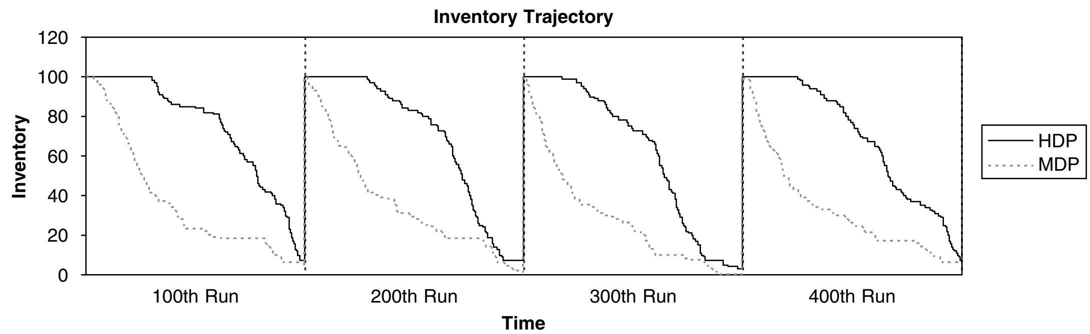


Figure 5: (a) Price trajectory for HDP/MDP in selected runs. (b) Inventory trajectory for HDP/MDP in selected runs

Table 5: Average utilisations for simulation runs in Table 4

	HDP/HDP		*HDP/EMSRb*		*HDP/Matching*		*HDP/MDP*	
High	0.890	0.894	0.835	0.999	0.870	0.860	0.906	0.980
Medium	0.888	0.873	0.886	0.935	0.836	0.832	0.873	0.942
Low	0.740	0.748	0.743	0.745	0.737	0.735	0.738	0.750

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