

Adaptive Strategies for Dynamic Pricing Agents

Sara Ramezani ^a

Peter A. N. Bosman ^a

Han La Poutré ^a

^a *CWI, Dutch National Institute for Mathematics and Computer Science
P.O. Box 94079, NL-1090 GB, Amsterdam, The Netherlands*

Abstract

Dynamic Pricing (DyP) is a form of Revenue Management in which the price of a (usually) perishable good is changed over time to increase revenue. It is an effective method that has become even more relevant and useful with the emergence of Internet firms and the possibility of readily and frequently updating prices. In this paper a new approach to DyP is presented. We design an adaptive dynamic pricing strategy and optimize its parameters with an Evolutionary Algorithm (EA) offline, while the strategy can deal with stochastic market dynamics quickly online. We design the adaptive heuristic dynamic pricing strategy in a duopoly where each firm has a finite inventory of a single type of good. We consider two cases, one in which the average of a customer population's stochastic valuation for each of the goods is constant throughout the selling horizon and one in which the average customer valuation for each good is changed according to a random Brownian motion. We also design an agent-based software framework for simulating various dynamic pricing strategies in agent-based marketplaces with multiple firms in a bounded time horizon. We use an EA to optimize the parameters of the pricing strategy in each of the settings and compare our strategy with other strategies from the literature. We also perform a sensitivity analysis and show that the optimized strategy works well even when used in settings with varied demand functions.

This is an extended abstract of work to be presented in The 2011 IEEE/WIC/ACM International Conference on Intelligent Agent Technology [3].

1 Introduction

Dynamic Pricing (DyP) is a form of Revenue Management (RM) that involves changing the price of goods or services over time with the aim of increasing revenue [4]. Today, the Internet provides exceptional opportunities for practicing RM and particularly DyP. This is both due to the amount of data available and the restructuring of price posting procedures. Thus, the Internet can facilitate offering different prices for different customers and posting new prices with minimum extra costs. This also allows for the increased use of intelligent autonomous agents in e-commerce, agents designed for automated buying, selling, price comparison, bargaining, etc.. We study dynamic pricing of a limited supply of goods in a competitive finite-horizon market. We design and implement an interactive agent based marketplace where the agents are the firms who wish to increase their revenue using dynamic pricing strategies.

2 Model and Method

We study a market consisting of two firms, each selling a limited inventory of a single type of good in a finite number of time steps. Each firm can adjust the price of a unit of its good in every time step. We assume that there is an unbounded population of customers that arrive sequentially and the number of customers that arrive in each time step follows a Poisson process. The customers' valuation for a unit of each firm's good has a Normal distribution. Each customer needs one unit of a good that can be obtained from either one of the firms; it purchases from the firm which has the highest utility (valuation minus price), given that this utility is not negative. We study two cases, one in which the customers' valuations for the products follow the same valuation throughout the selling horizon and one in which the average of their valuations follow a random Brownian motion over time.

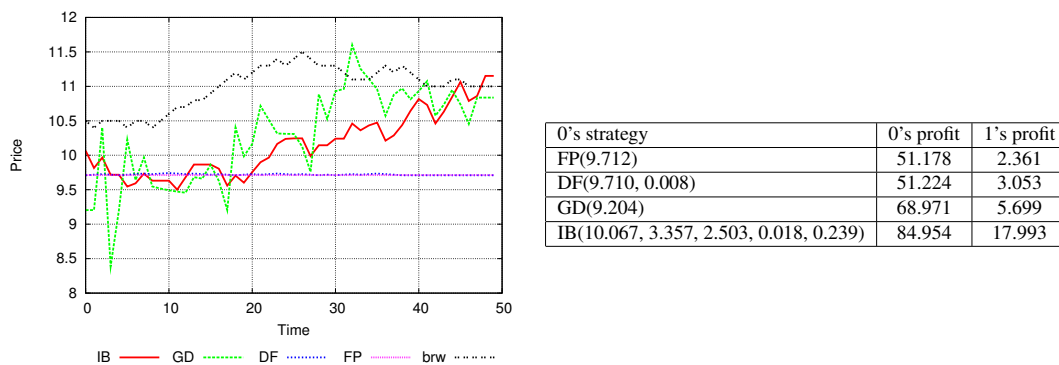


Figure 1: Left: Illustration of the prices set by strategies in a single instance. Right: Comparison of profits obtained from strategies with Brownian motion.

We design an adaptive heuristic dynamic pricing strategy for a firm in such a marketplace, called the *Inventory Based Strategy (IB)*, that aims at finishing the inventory by the end of the time horizon. In each time step, the firm estimates the number of goods that will be sold, given the average customer arrival rate and the rate at which the firm sold its goods in the previous time step. It then changes the price depending on how far this estimate is from the number of goods left in the inventory. There are limits on the percentage that the price can increase or decrease during each time step, designed to guarantee some price stability and as a protection against sudden jumps due to stochasticity. There are also thresholds in which the price will not change, if it is close enough to the desired result. These two kinds of parameters, along with the price in the initial time step are the parameters of the strategy. We have designed software to simulate a marketplace described above and implemented the IB strategy in such a marketplace, where one agent uses the heuristic strategy and the other uses a fixed price strategy. We use an Evolutionary Algorithm (EA), AMaLGaM [1], to numerically optimize the parameters for the strategy, using our simulation as a black-box.

3 Experiments and Results

We run the EA multiple times for each of the Brownian and non-Brownian cases. The parameter sets obtained from these runs were cross evaluated and the one yielding the best result in each case was selected. The results from IB are compared with results from a fixed price strategy, various derivative follower strategies from the literature and a heuristic Goal Directed (GD) strategy from [2]; the parameters for all of these algorithms are optimized using the same EA and method. We show that IB consistently outperforms the other strategies, with much better results for the Brownian case and a smaller difference with the GD strategy. The results can be shown to be statistically significant.

Furthermore, we assess the robustness of the method and show that it still performs well when wrong assumptions are made about the market configuration. We perform sensitivity analysis experiments to observe the amount of profit loss if the previously optimized parameters are used in a configuration where the demand rate has changed from %80 to %160 and compare that to the results where the demand is optimized for the new configuration. It is shown that the profit loss in all of these cases is always smaller than %10.

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