

# Data-Driven Repricing Strategies in Competitive Markets: An Interactive Simulation Platform

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## ABSTRACT

Modern e-commerce platforms pose both opportunities as well as hurdles for merchants. While merchants can observe markets at any point in time and automatically reprice their products, they also have to compete simultaneously with dozens of competitors. Currently, retailers lack the possibility to test, develop, and evaluate their algorithms appropriately before releasing them into the real world. At the same time, it is challenging for researchers to investigate how pricing strategies interact with each other under heavy competition. To study dynamic pricing competition on online marketplaces, we built an open simulation platform. To be both flexible and scalable, the platform has a microservice-based architecture and handles large numbers of competing merchants and arriving consumers. It allows merchants to deploy the full width of pricing strategies, from simple rule-based strategies to more sophisticated data-driven strategies using machine learning. Our platform enables analyses of how a strategy's performance is affected by customer behavior, price adjustment frequencies, the competitors' strategies, and the exit/entry of competitors. Moreover, our platform allows to study the long-term behavior of self-adapting strategies.

## KEYWORDS

dynamic pricing; simulation; oligopoly competition; demand learning; microservice architecture

## 1 SIMULATING PRICING COMPETITION

Online marketplaces are highly dynamic and competitive. Merchants are allowed to automatically adjust prices to react to changing market situations. To derive effective pricing strategies is challenging considering that thousands of products have to be managed and demand information is limited (cf. Chen and Chen [1]).

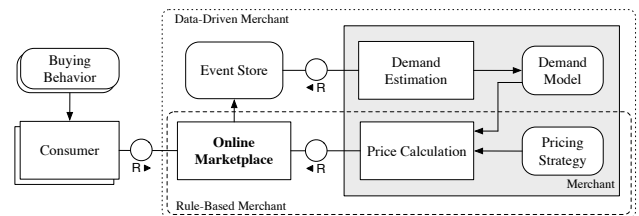
As testing automated pricing strategies is potentially hazardous when done in production, simulating the performance of competing repricing strategies is important. However, little effort has been made to build flexible simulation platforms that ease the development and evaluation of repricing algorithms. Existing platforms, e.g., [2], are limited in their capabilities: Simulations run on a single machine, offer a limited set of consumer behaviors, simulate solely

finite sales horizons, and pricing updates are restricted to discrete points in time that are predefined by the system.

In other areas simulation platforms are also used to study complex systems, e.g., in the field of real-time bidding [8], marketing [5], or electricity markets [3].

We built a continuous time framework (mimicking production marketplaces such as Amazon or eBay) to simulate dynamic pricing competition for the sale of durable goods. This setup allows to define a random stream of potential customers whose buying decisions for a specific product can arbitrarily depend on the current market situation determined by the competitors' offers which include price and quality. Evaluating the mutual price reactions of competing strategies, we obtain price trajectories and simulate realized sales events. By visualizing various performance measures (e.g., short and long-term profits), the user can easily compare different types of repricing strategies.

Our simulation marketplace has an HTTP/REST-based interface. That enables our platform to allow an arbitrary number of merchants to compete simultaneously. Each merchant can run his preferred repricing strategy to adjust prices on the marketplace. The platform logs each interaction (such as price updates, new offers, sales, etc.), which can be requested and analyzed by each merchant. This way, merchants can deploy both rule-based strategies as well as data-driven strategies that leverage various demand learning approaches to estimate customers' buying behavior (Figure 1 depicts the platform's components for both pricing strategies).



**Figure 1: Platform architecture showing the different components used by rule-based and data-driven merchants (FMC notation [6]).**

Our framework also makes it possible to measure the influence of the customers' buying behavior, price adjustment frequencies, and the exit or entry of competitors on a strategy's performance. In addition, demand learning techniques can be compared regarding their accuracy and efficiency.

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## 2 DESCRIPTION OF THE PLATFORM

The platform was built with a microservice-based architecture for scalability and flexibility. Each service implements one business artifact, whereby services can be scaled out for large simulations. By having separated services, additional components can be added during running simulations at any time.

Most importantly, merchants can be easily added to the simulation or updated as long as they confirm to the HTTP/REST interface of the platform. Merchants update their products' prices based on the current market situation which they can request at any time. Arbitrary strategies, e.g., rule-based or data-driven strategies, can be applied. Data of observed market situation as well as a merchant's sales data can be used to estimate sales probabilities using various machine learning techniques (e.g., Q-learning [7]).

The centre of the simulation is the *marketplace* which manages all product offers. Offers include price and quality. The marketplace is the access point for the *consumer* component which creates a random stream of interested customers. Any customer choice behavior can be defined. The decision whether a customer buys a product and which offer is chosen, is modelled by probabilities that can depend on all parameters of the current market situation. The *log store* logs platform events (e.g., price adjustments and sales) and provides CSV files for data-driven merchants. The *producer* is responsible for the replenishment. Merchants are provided with new products according to a (fair) distribution. This way the performances of competing strategies are not affected by asymmetric reordering strategies. However, the model also allows to let merchants choose their replenishment on their own. The *HTML-based front end* enables the user to configure customer behavior, merchants, as well as replenishment rules.

The front end shown in Figure 2 allows to observe the evolution of market situations and price trajectories over time. The strategies' short-term and long-term performances are measured by different KPIs, including profits, revenues (see Figure 3), sales, etc.

A detailed description of the platform, its architecture, and the components can be found in [4].

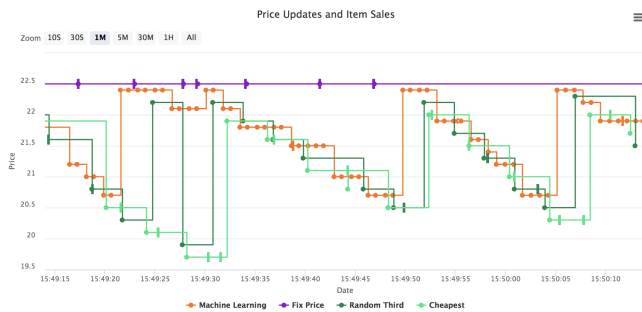


Figure 2: Competitors' price trajectories over time.

## 3 RESULTS

The platform allows to simulate strategic interaction of various rule-based and data-driven strategies in different market scenarios characterized by product portfolios, customer behaviors, oligopoly

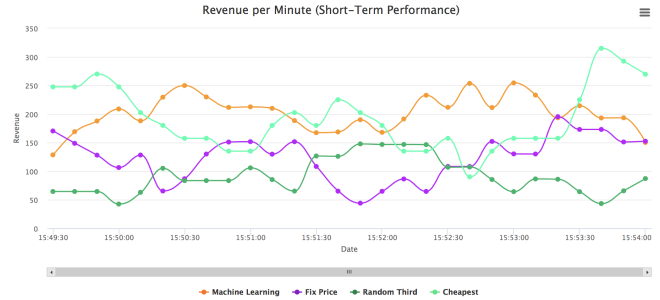


Figure 3: Comparison of short-term revenue (moving window aggregation over last minute) over time.

settings, and price adjustment frequencies. We found that adjustment frequencies have a major impact on expected profits and data-driven strategies often vastly outperform rule-based ones after a sufficiently large data set has been gathered. Moreover, the platform can be used to study short-term as well as long-term performance of self-adapting strategies that iteratively improve their pricing strategies.

## 4 CONCLUSION

The presented dynamic pricing simulation is a distributed and scalable platform mimicking real-world e-commerce applications. With this toolkit, both practitioners and researchers can directly participate and study various pricing strategies under competition and develop, test, and evaluate own approaches. Furthermore, our model can be easily extended in several ways: (i) additional offer dimensions (ratings, shipping time, etc.), (ii) joint replenishment decisions for sellers, (iii) the consideration of perishable products, and (iv) substitution effects between different products.

The source code and its technical documentation is publicly available at GitHub<sup>1</sup>. A screen cast of the simulation is available under <https://vimeo.com/epicchair/pricewars>.

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<sup>1</sup>Platform repository: <https://github.com/hpi-epic/masterproject-pricewars>