Exploring PRDE Trading Strategies in a Model Dynamic Financial Market

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***Abstract*—In this paper, we experiment with fifty-two different parameter combinations of PRDE strategies and simulate them in continuous double auction markets. PRDE is a co-evolutionary strategy that modifies the PRSH strategy using Differential Evolution (DE). During the continuous double auction simulation, we use the Bristol Stock Exchange(BSE) simulation system to conduct the experiments and to visualize the data. The BSE trails use different combinations of PRDE parameter(k, F) for the simulation auction to find a best parameter selection strategy. The paper gives the results and visualization conclusions of this experiment at the end.**

***Index Terms*—Automated Trading; Co-Evolution; Financial Markets; Zero-Intelligence Traders; Differential Evolution**

I. INTRODUCTION

The topic of stock trading using financial agent traders has been of great interest in the past decades in both academic and practitioners' studies. Due to the development of financial technology, there are many adaptive automated trading systems in the actual financial system. These trading agents do not exist in isolation; they all evolve continuously in trading to maximize their interests, so modern financial markets are co-evolutionary systems [1].

Bristol Stock Exchange (BSE) is an open-source continuous simulation system with predefined ZIC, ZIP, PRZI, PRSH, and PRDE proxy trading strategies [2]. The agent traders in BSE can trade through limit order book (LOB) and simulate continuous double auctions. BSE can simulate static markets or a variety of dynamic market trading, and has a fast running speed.

ZIC is a trading strategy that restricts only the upper and lower price limits for random bids. PRZI improves on ZIC by controlling the trading preferences of agent traders through parameters. Further, PRSH uses Hillclimber's evolutionary algorithm to improve ZIC to self-adapt to the market. The PRDE strategy explored in this paper is an adaptive algorithm similar to PRSH [1]. PRDE is shown to be twice as profitable as the PRSH trading strategy under certain parameters. Therefore, this experiment is conducted to simulate more parameter pairs to find a better combination of parameters.

Section II outlines the background of this paper, including a brief description of PRZI and PRSH and details of PRDE. Section III explains the motivation for the design of this experiment and how the BSE is used to simulate dynamic financial markets. After that, Section IV gives the results and the conceptualization of the above experiments. Finally, Section V concludes the paper and gives potential research directions for the paper.

II. BACKGROUND

A. Continuous Double Auction(CDA)

The secrecy of trading strategies in real financial markets and the high volume of transactions makes it difficult to test strategies in real exchanges. Therefore, researchers usually use a small number of traders in a continuous double auction to simulate actual trading.

Gode & Sunder used "zero-intelligence" programs instead of human traders in their study firstly [3]. They use this approach to simulate ZIC strategies to obtain data and achieve good results. Based on Gode & Sunder's research, Cliff proposed a trading strategy called ZIP, which proved more profitable than human traders [4].

B. Parameterized-Response Zero Intelligence(PRZI)

Parameterized-Response Zero Intelligence(PRZI) is an extension of the ZIC strategy and inherits the ZIC pricing model. However, unlike ZIC, which is characterized by random bids within price limits, PRZI allows agent traders to have particular trading preferences (easier to deal or more profitable).

PRZI introduces parameter $s \in [-1, +1]$ to control the profitability mass function (PMF) used to generate quote prices [5].

When s=0, agent traders do not have a trading preference, i.e., PRZI degenerates to a ZIC strategy. When $s \to -1$, it means that traders have a higher profit-taking preference, and the quote prices will be far away from the trader's limit price. In contrast, when traders prefer to trade, PRZI parameter s can be set closer to +1, i.e. $s \to +1$.

C. Co-evolution with Stochastic Hillclimbing(PRSH)

Although PRZI introduces the setting of trading preferences, such trading preferences are fixed throughout the process. Therefore, Cliff proposed an improved strategy based on PRZI, called PRSH (see [6]), in 2022.

PRSH introduces a hillclimber's evolutionary algorithm to achieve automatic market adaptation of agent traders [6]. PRSH uses the parameter k to denote the number of strategies.

During the trading process, PRSH continuously evaluates the current profitability and selects the strategy with the highest return as the elite strategy, while the remaining $k-1$ strategies are generated by adding noise to the elite strategy. The above evolution will be cycled through the trade to maximize overall profitability.

D. Co-evolution with Differential Evolution(PRDE)

PRDE uses Differential Evolution (DE) to replace the Hillclimber evolutionary algorithm in PRSH. PRDE maintains a local population with the populaton number NP, where $NP \geq 4$ (NP can be approximated as the parameter k in PRSH) [1].

When PRDE generates a new mutation vector, it uses differential evolution, which is an evolutionary algorithm with better convergence [7]. Its mutation process can be summarized in the following mathematical representation

$$v_{i,G+1} = x_{r_1,G} + F \cdot (x_{r_2,G} - x_{r_3,G})$$

with $i \in \{1, 2, 3, \cdots, NP\}$ and $F \in [0, 2]$ [7]. PRDE can use the parameter F to control the degree of variation in each loop, and in general, increasing the value of F can slow down the convergence of DE.

In Cliff's study [1], it was shown that the PRDE model had better performance compared to PRSH.

III. EXPERIMENTAL DESIGN

This experiment uses the Bristol Stock Exchange (BSE, see [2]) to simulate the PRDE strategy.

The simulating trails use 10 PRDE buyers and 10 PRDE sellers placing orders 5 seconds apart. For transactions with k values of 4 and 5, the parameter $F \in \{0.1, 0.2, \cdots, 1.9\}$, simulating 96 hours of trading. Due to the time problem, the parameter F is set to $\{0.1, 0.2, \cdots, 1.3\}$ for transactions with $k = 6$, simulating 96 hours of trading.

Since sudden price increases or decreases can occur in real financial markets, this is called market shock. Therefore, in the design of the experiment, the trading time is divided equally into three periods. The supply and demand schedules for each segment are defined as $price1 \in [50, 100]$, $price2 \in [150, 200]$, $price3 \in [220, 280]$. The supply and demand curves when the market is shocked is shown in Figure 1.

The data needed for this experiment are saved in csv files and named in $kvalue\_Fvalue\_trails\_trail\_avg\_balance.csv$ format. Average PPS is calculated using the total revenue and time in it, i.e. $avgPPS = \Delta Profits/\Delta Time$.

Running on a Azure Virtual Machine with Standard B1ms (1 vCPU, 2 GiB memory), the simulating trails with fifty-two different parameter combinations took about 52 hours of wall-clock CPU time.

The code used in this experiment will be open sourced on Github after January 10, 2023.

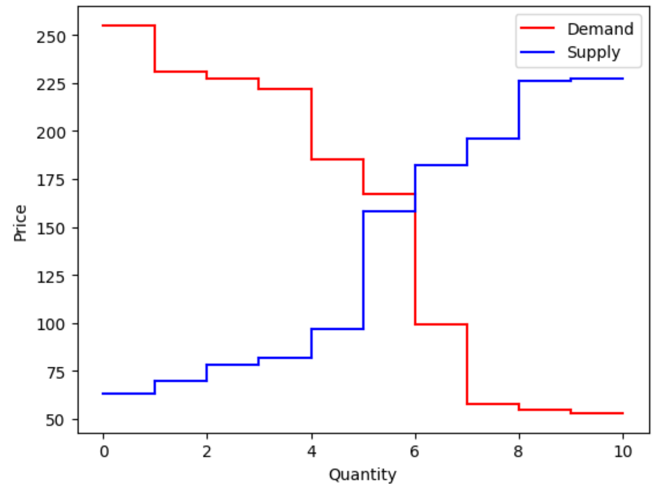

Fig. 1. Simulate the supply and demand curves in the event of a market shock, with buyers and sellers set to ten respectively.

IV. RESULT

A. Exploring the Effect of Parameter k

First, this section measures the strategy in terms of average profit per second (avg PPS).

Figure 2 shows the density distribution of average PPS for $k = 4, 5, 6$, respectively. It can be seen that the peaks of all three curves are concentrated at $avg\_PPS \in [14.5, 15.0]$, but the k4 curve as a whole and the peak are more to the right, i.e., have better returns.

The k5 curve has the smallest tail, which means that the high returns at $k = 5$ are more concentrated. The worst performer is the k6 curve, which may be due to the DE not converging. The study can be continued for an extended period of time in subsequent experiments.

Figure 3 shows the violin plot for different values of k. The narrowest k6 curve also expresses the dispersion of its profits. The best performer is still the k4 curve, whose returns are more concentrated at the high end.

Therefore, the best overall performance in this experiment is $k = 4$, but there may be individual examples of high returns for $k = 6$.

B. Exploring the Effect of Parameter F

Figure 4 is a box plot plotted for all F values, which shows the quartiles of the corresponding data set. It can be seen from Figure 4 that F1.7 has a small low PPS and is concentrated above 14.5. Also, the overall gain of $F \in \{0.4, 0.7, 1.1\}$ is better.

For the PPS data set of $F \in \{0.4, 0.7, 1.1, 1.7\}$ is extracted separately to plot the violin plot shown in Figure 5. The best return is also F1.7, and is concentrated in the high end. In addition, F0.7 also performs better because it does not have low values like $F \in \{0.4, 1.1\}$.

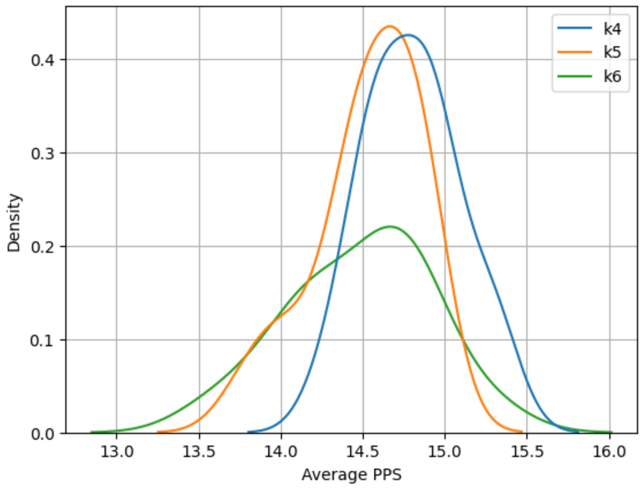

Fig. 2. Kernel density estimate (KDE) plot of Average PPS. This figure uses different curves to represent parameter k, the horizontal coordinate represents Average PPS, and the vertical coordinate represents the corresponding probability density of average PPS for the same k value.

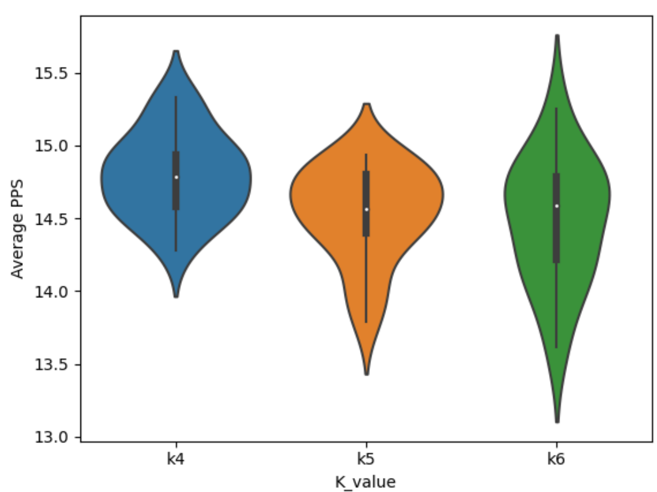

Fig. 3. The violin plot of average PPS. The horizontal axis indicates different k value $k \in \{4, 5, 6\}$.

C. Analyzing Individual Cases of Significant Profits

The average PPS for all parameter pairs is shown in Figure 7. From Figure 7, it can be seen that the average PPS with $(k, F) \in \{(4, 1.7), (4, 0.7), (6, 1.1)\}$ are higher than others. The control group used the $(k, F) = (4, 0.8)$ from Cliff's study, which proved to be better than the PRSH model [1].

Figure 6 shows the 4-hour moving average PPS for the four parameter pairs. Although the experimental group outperforms the control group at the beginning, the highest gain is lower than the control group. And there are cases of missing values, so the experiment will be repeated in the later experiments to judge the performance of these parameter pairs.

In this part of the experiment, the judging criteria for different pairs of parameters were set to average profits. Since the convergence of PRDE takes some time, the total average

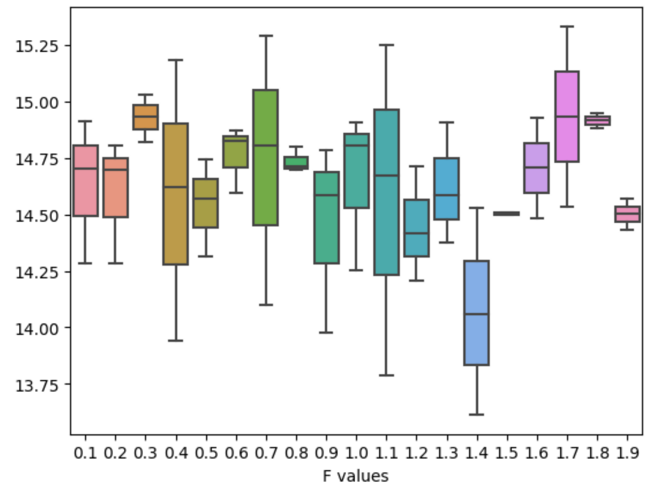

Fig. 4. The box plot of average PPS. The horizontal axis indicates different F value $F \in [0.1, 1.9]$.

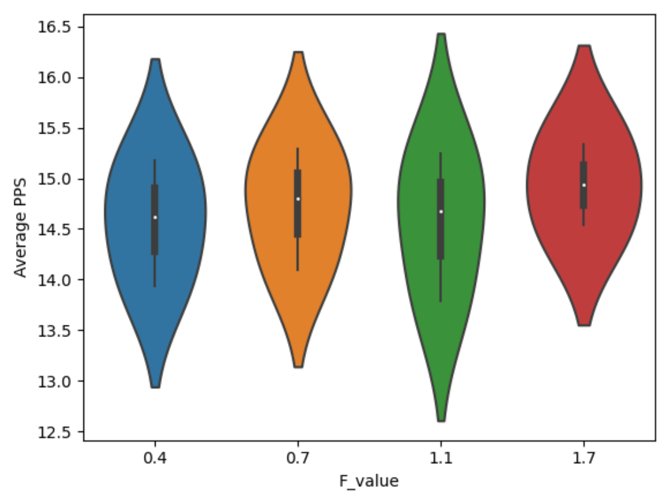

Fig. 5. The violin plot of average PPS. The horizontal axis indicates different F value $F \in \{0.4, 0.7, 1.1, 1.7\}$.

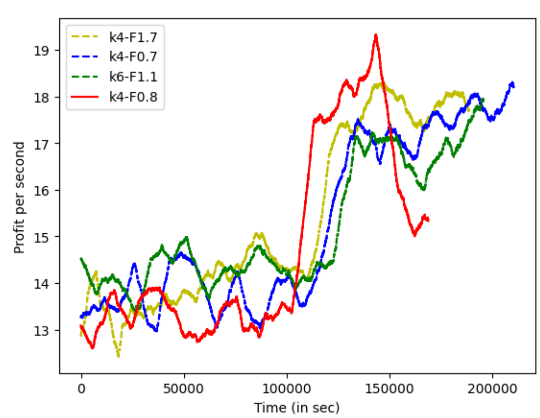

Fig. 6. 4-hours moving average PPS of four specific pairs of parameters.

TABLE I
OVERVIEW OF STATISTICS FOR THE FOUR DATA SETS

Average Profits Statistics	Experimental Group			Control Group
	(k, F) = (4, 1.7)	*(k, F) = (4, 0.7)*	*(k, F) = (6, 1.1)*	*(k, F) = (4, 0.8)*
Mean	236666	248047	241523	214697
Median	236672	248054	241521	214694
Std	389	333	373	408

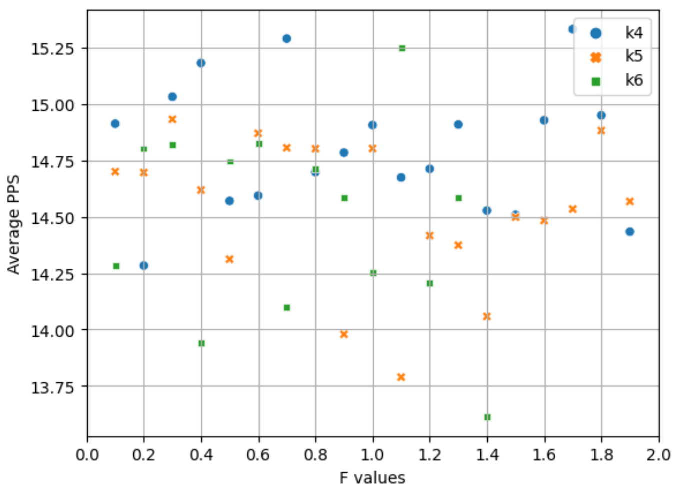

Fig. 7. The distribution of Average PPS while taking different values of the parameters pair k, F.

profit of the last 1000 trades was selected as the data set. This also avoids the inaccuracy of the Shapiro-Wilk test when testing the normal distribution for data sizes larger than 1000.

The first step of the experiment used the Shapiro-Wilk test to test whether the four data sets follow a normal distribution. The results of the test were that the null hypothesis of normal distribution was rejected, i.e., they did not follow normal distribution.

The non-normal distribution is usually analyzed using the Mann-Whitney U test for the distribution of the two data sets. The p-values for the three control experiments in this paper were all less than 0.05, so the null hypothesis of having same distributions was rejected.

In Table I, it can be seen that the mean and median of the three experimental groups are higher than those of the control group, and the standard deviation is smaller than that of the control group. Combined with the rejection of the original hypothesis at the Mann-Whitney U test, it can be concluded that the experimental group performs better than the control group in terms of average profit.

The profit data of the best-performing parameter pair $(k, F) = (4, 0.7)$ in the experimental group was selected for the Mann-Whitney U test with the profits of the other two parameter pairs $(k, F) \in \{(4, 1.7), (6, 1.1)\}$, respectively. The test results were all p-values less than 0.05, meaning that this parameter pair $(k, F) = (4, 0.7)$ performed significantly better than the other three data sets.

V. DISCUSSION AND CONCLUSION

In this paper, a simulation of Cliff's PRDE model was conducted using the Bristol Stock Exchange (BSE). The experimental procedure replaces real exchange trading with a continuous double auction(CDA). Fifty-two different parameter pairs are used in the BSE simulation, and 96 hours of real trading are simulated in each transaction.

One of the contributions of this paper is to explore the effect of parameter k and parameter F on the trading results of the PRDE model, respectively. It can be seen that the better choice among $k \in \{4, 5, 6\}$ is $k = 4$, and several better-performing choices for parameter F values are given.

Another contribution is the analysis of the three groups with significant profits among these 52 parameter pairs. These three experiment groups were tested with control group ($(k, F) = (4, 0.8)$) using the Mann-Whitney U test. It was observed that in the setting of this paper, PRDE has the best average profit using parameter pair $(k, F) = (4, 0.7)$.

However, due to time constraints, the experiment was not repeated for each group of data in this paper, and thus there may be cases of outliers. For example, it would be better to repeat trials multiple times to test the total profit for each set of data for individual case analysis. Also, this paper does not analyze the cases where the parameter k is greater than 6, since this requires a longer convergence time. Therefore, further improvement of this paper should be to increase the number of experiments and time period, and then to analyze larger local populations(i.e., $k \geq 7$).

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