# Finding the optimum parameters for a Parameterised Response Differential Evolution trading strategy

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***Abstract*—In this report, we introduce an adaptive trading strategy called *Parameterised Response Differential Evolution*(PRDE) [1], and evaluate the optimum parameters by running a series of experiments on the Bristol Stock Exchange. It is then attempted to further extend this algorithm.**

***Index Terms*—Automated Trading, Financial Markets, Adaptive Trader-Agents, Optimization, Multi-Armed Bandits, Bristol Stock Exchange**

## I. Introduction

In 2001, it was demonstrated that automated traders can persistently outperform human traders [2], using extensions of the Gjerstad-Dickhaut and Zero-Intelligence-Plus algorithms. Since then, most of the world's major financial markets have been dominated by automated traders. As such, there is an ongoing effort to design trading strategies that maximise profits and outperform competition. One such algorithm is the Parameterised Response Differential Evolution.

## II. Bristol Stock Exchange

The Bristol Stock Exchange [3] is a simple simulation of an electronic financial exchange based on a continuous double auction(CDA) running via a limit order book. The CDA is in fact the dominant institution for real-world trading equities, commodities and derivatives. Rather than operating by regurgitating a time-series database of historical transaction prices as in traditional financial-market simulators, prices in BSE are directly dependent on the actions and interactions of the traders active in the market, and is thus a much better simulation of a financial market.

BSE can be populated by a variety of automated trader-agents, and comes with a number of pre-coded robot trading algorithms. These robot traders are either adaptive, in which they alter their trading behavior in response to market conditions, or non-adaptive, issuing their bids and/or asks at time and prices set by their internal algorithm that does not alter over time. We will thus use BSE to run a series of experiments to determine the optimum parameters for a PRDE trader.

## III. Parameterised Response Differential Evolution

Before discussing the experiments, we must first introduce the Parameterised Response Differential Evolution (PRDE, pronounced "purdie") trading strategy. PRDE uses a widely-used optimization technique called Differential Evolution (DE). PRDE is built upon the Parameterized-Response Zero-Intelligence (PRZI) trading strategy and it stands to reason that we first discuss PRZI.

### A. Parameterized-Response Zero-Intelligence

The Parameterized-Response Zero-Intelligence [4] algorithm is a new form of zero-intelligence trader. Similar to Gode & Sunder's classic Zero-Intelligence Constrained (ZIC) [5] trader, this strategy generates random quote prices constrained to a specified domain so as to not make a loss. While ZIC uses uniform distribution to generate prices, a PRZI trader has a control variable $s \in [-1.0, +1.0] \in \mathbb{R}$ to determine its probability mass function (PMF), and hence the strategy for that trader. Depending on its specific value of s, a PRZI trader might behave like SHVR, ZIC, GVWY (all of which are Zero-intelligence traders), or like some hybrid mix of those strategies. An individual PRZI trader is defined to keep the same s value for as long as it exists, i.e. it is non-adaptive. As such, there have been attempts to extend PRZI to incorporate adaptivity. The first such attempt is Parameterised Response Stochastic Hill-climber (PRSH), which uses a very simple stochastic hill-climbing method.

### B. Parameterised Response Stochastic Hill-climber

A PRSH trader [4] adapts its value of s over time via a very simple stochastic hill-climbing method. At any time t, a PRSH trader has a set K containing k different values of s. The trader operates on an infinite loop, where in each cycle of the loop, it evaluates each of its k strategies by trading in the market using each s value for a specific period of time, and find the top performing strategy, $s_0$, which is used to create k - 1 "mutations" of $s_0$, typically by adding a small amount of Gaussian noise. This new set of K values is then used for the next iteration of the loop. Unfortunately, this method is very inefficient, and so an improved attempt to add adaptivity to PRZI, but with better efficiency has given rise to the PRDE trading algorithm.

### C. Parameterized Response Differential Evolution

A PRDE trader maintains its own private local population of trading strategies, and uses a very basic form of a widely-used optimisation technique, called Differential Evolution (DE), to adaptively improve its strategies over time. There are 2 notable parameters:

1) Number of different candidate solutions, k, represents the number of different candidate solutions. The first and simplest form of DE, which is what is used in PRDE, requires that $k \geq 4$.
2) Differential Weight, denoted by F, is a coefficient which controls the extent to which the difference between two candidate solution vectors is mixed in with a base vector (essentially, another candidate solution randomly drawn from the population). This value is usually set to $0 \leq F \leq 2$.

The implementation of PRDE on GitHub [6] has values k=4 and F=0.8. However, these may not be the optimal values and so we explore how different choices of these parameters affects the trader's behaviour.

## IV. Experimental Setup

### A. Types of traders

Given the parameter restrictions set out above, every combination of values k in the range 4 to 10 and values F from 0 to 2.0, in steps of 0.1 in the latter case are initially trialed. This gives a total of 147 possibilities. This would clearly be a lot of experiments to run, especially if this were to be run for multiple trials and for different market environments. As such, these 147 parameters are only run once in a static homogeneous market - that is, a market where the supply and demand curves are deemed to be fixed and is made up of purely 1 type of trader. Given the results of this set of experiments, a maximum of 15 traders were extracted by selecting the 5 best buyers, sellers and overall traders, and subsequent experiments are run with these 15 traders only, massively decreasing the number of experiments needed to be run, while not overly constraining the range of possible values for F and k.

### B. Market Environments

Depending on the commodity traded, the supply and demand may be largely static, with near-fixed supply and demand curves, or at least long periods of stability. In such an environment, it would therefore be useful to see how the trading agents perform.

However, there may also be other commodities that are highly volatile, or scenarios in which unforeseen events causes a market shock, dramatically increasing or decreasing supply and/or demand. As such, we introduce market shocks during the experiment to demonstrate how well the traders respond to sudden changes in the market.

Additionally, trading markets are highly unlikely to be made up of purely 1 type of trader and so we experiment on heterogeneous markets where multiple types of traders are present, and analyse how each different type of trader fares. Following the methods used by IBM [7], we perform sets of one-in-many tests, in which 1 trader in a homogeneous population defects. If this 1 trader performs better, one could expect the entire population to eventually defect to the other strategy. Otherwise, the defector would return to the original strategy given that it aims to maximise its profits, and the market returns to a perfectly homogeneous population.

### C. Elasticity of Supply and Demand

Reproducing the experiments discussed in the paper which first introduces PRDE [1], we first assume that all buyers are instructed to pay no more than \$140 per unit when purchasing, and that all sellers are instructed to sell for no less than \$60 per unit. This means that in principle every seller can find a buyer (and vice versa) who is able to be a counter-party to a transaction.

This is not an unrealistic assumption to make. When all buyers are instructed to pay no more than \$140 per unit, this means that graphically the demand curve would be a horizontal line at \$140. Above this level, demand would become non-existent, while below that level, those buyers would purchase as many units as available. In other words, the demand schedule is perfectly elastic at the unit price of \$140. Conceptually speaking, this unit price of \$140 serves as a break-even point for the traders. Hence, they would not make any purchase at all, if the price exceeds \$140, because they would incur losses. However, it would maximise their gains to purchase the units as long as the price is less than \$140, even though the lower the price, the more profitable the transaction would be. The same logic applies to sellers.

### D. Experiment Specifications

Unlike the PRSH traders, which had an initial adaptive transient of around 25 days [1], this period is much shorter for PRDE traders at less than 15 hours. As such, each experiment is run over the course of 3 days, favouring running more experiments to analyse a range of different market conditions, over longer trading windows. Due to the partially stochastic nature of the results, each experiment is also trialed 5 times and averaged. Additionally, each market is populated with 30 buyers and sellers.

Orders are replenished with a 'drip-poisson' timemode as in reality, new orders will not be given to traders in a regular fashion. There is an additional parameter, stepmode, which tells BSE how to space out the prices of orders it gives to traders. However, as we are assuming perfectly elastic supply and demand, the stepmode has no effect.

## V. Results

### A. Static Homogeneous Market

As set out in IV-A, each possible combination of the parameters k and F experiments are initially tested to determine the top traders to run subsequent simulations on.

Figure 1 shows the simple moving average profitability of the trader with the highest overall profitability with parameters set to F=2.0 and k=4.0. There is an initial adaptive transient period of around 10 hours. The length of this period varied with different traders, but it was seen to be at a maximum period of 15 hours. Given that robot traders are expected


Fig. 1: Plot of profitability data from one 3-day experiment in a market populated entirely by PRDE traders with F=2.00 and K=4, calculated by the simple moving average of profit per second (PPS) over the preceding 5 hours.

to populate real-world markets for long periods of time, the profitability of the initial transient period would be negligible. However, as simulations are only run for 3 days at a time, we disregard the transient period in order to diminish its effect on the results when comparing traders, and hence exclude the first 15 hours of the simulations when calculating the total PPS. Interestingly, profit of buyers seems to be much higher than the seller traders.

To illustrate the comparative profitability of the different traders, Figure 2 shows 3 different heat-maps of the profitability. As evident in Figure 2a, the most profitable traders tended to have low k and F values. In comparison, Figure 2b shows that the most profitable sellers also had lower values of k but higher F values. The overall profitability is shown in the final heat-map in Figure 2c, which seems to follow a similar patter to 2b. This is likely due to the higher profits generated by buyers, leading to a much larger weight of the overall profitability.

Using these results, we are able to extract the parameters of the top 5 most profitable buyers, sellers and overall traders, as listed in Table I. As 2 parameters are repeated over the 3 categories, this gives 13 different traders, which we use for subsequent experiments. Notably, over half of these 13 traders have value k=4 and other values of k tend to be relatively small.

TABLE I: Parameters of the Top 5 most profitable traders in each category

| | Buyer | | Seller | | Total | |
|---|---|---|---|---|---|---|
| **Rank** | **k** | **F** | **k** | **F** | **k** | **F** |
| 1 | 4 | 0.2 | 5 | 1.9 | 4 | 2.0 |
| 2 | 4 | 0.1 | 4 | 2.0 | 5 | 2.0 |
| 3 | 4 | 0.7 | 6 | 2.0 | 4 | 1.6 |
| 4 | 6 | 0.4 | 4 | 1.7 | 7 | 2.0 |
| 5 | 4 | 0.5 | 7 | 2.0 | 5 | 1.8 |


(a) Heat-map of Buyers' Profits


(b) Heat-map of Sellers' Profits


(c) Heat-map of Total Profits

Fig. 2: Heat-map of profitability over the different parameters tested

Repeating and averaging the results across 5 trials yields the data as shown in Figure 3. Consistent with the results when only running 1 trial (Table I), buyers performed well with k=4, while sellers tended to have high values of F. Table II shows that the top 5 sellers all had values of $F \geq 1.7$. Yet again, the discrepancy between the profit generated between buyers and sellers causes the parameters of the top 5 traders to be biased towards the sellers.

### *B. Dynamic Homogeneous Market*

As discussed in section IV-B, further experiments were conducted to see how traders responded to a shock in the market. Starting off with perfectly elastic supply and demand curves priced at \$60 and \$140 respectively (as in section V-A), the market experiences a shock a third of the way through

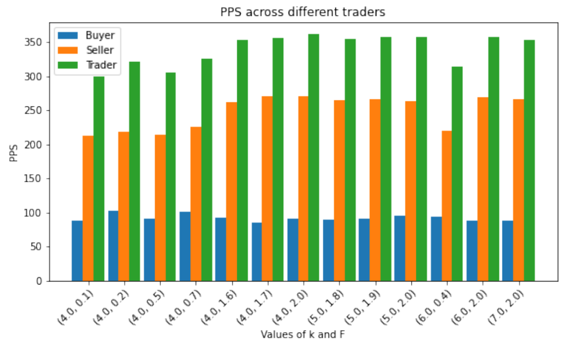



Fig. 3: Plot of PPS for 3-day experiments averaged over 5 trials in a market populated entirely by PRDE traders with different k and F values

TABLE II: Parameters of the Top 5 most profitable traders in each category from each experiment repeated over 5 trials

| | Buyer | | Seller | | Total | |
|---|---|---|---|---|---|---|
| **Rank** | **k** | **F** | **k** | **F** | **k** | **F** |
| 1 | 4 | 0.2 | 4 | 1.7 | 5.0 | 1.9 |
| 2 | 4 | 0.7 | 6 | 2.0 | 5 | 2.0 |
| 3 | 5 | 2.0 | 5 | 1.9 | 6 | 2.0 |
| 4 | 6 | 0.4 | 7 | 2.0 | 4 | 1.7 |
| 5 | 4 | 1.6 | 5 | 1.8 | 5 | 1.8 |

the experiment, causing the buyer limit price to rise to $180, while the seller limit price rises to $140 before returning to the original supply and demand conditions in the last third of the trading window.

Figure 4 shows an example of the simple moving average of the PPS when K=4 and F=1.70. Following the market shock (marked by the 1st dotted red line), there is a dip in the profit generated by sellers before they are able to adjust to the new prices. Correspondingly, the buyers see an increase in their profits as they are able to buy at a relatively high price compared to their new limit price.


Fig. 4: Plot of the SMA over preceding 5 days of PPS in a 3-day experiment averaged over 5 trials in a market populated entirely by PRDE traders with K=4 and F=1.70 in a dynamic homogeneous market

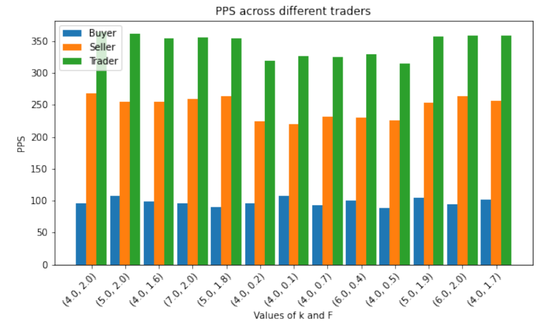



Fig. 5: Plot of PPS 3-day experiments averaged over 5 trials in a market populated entirely by PRDE traders with different k and F values

Figure 5 shows the average PPS for the different traders, with a similar trend to that of the static homogeneous market. In the current dynamic environment, the values of k at which buyer traders performed the best remained at a value $\leq 5$, while k values remained at the top end of the spectrum for the sellers.

Table III shows the average PPS of the different traders and also for the sub-population of buyers and sellers. The difference in the PPS generated in this market are also compared to that of the PPS generated from the experiments in the static homogeneous market. We can see that in general the buyer traders responded better to the market shock, with most of the buyers yielding a higher PPS, while sellers performed comparatively worse.

TABLE III: PPS of the traders in a dynamic homogeneous environment, with the difference in PPS compared to that of the experiments conducted in a static homogeneous market

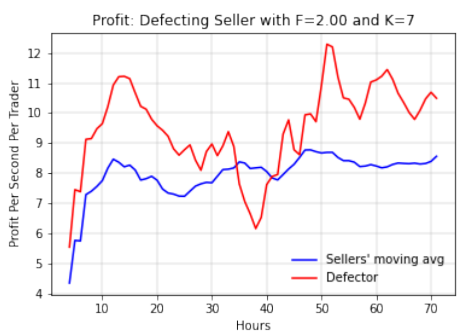
| k | f | buyer | buyer diff | seller | seller diff | buyer | diff |
|---|---|---|---|---|---|---|---|
| 4.00 | 0.10 | 107.24 | 19.87 | 219.73 | 6.85 | 326.97 | 26.72 |
| 4.00 | 0.20 | 95.52 | -7.16 | 224.28 | 6.18 | 319.80 | -0.98 |
| 4.00 | 0.50 | 89.06 | -2.20 | 225.18 | 11.12 | 314.24 | 8.92 |
| 4.00 | 0.70 | 92.75 | -8.61 | 231.66 | 6.62 | 324.41 | -1.99 |
| 4.00 | 1.60 | 99.46 | 7.88 | 255.04 | -7.07 | 354.50 | 0.81 |
| 4.00 | 1.70 | 102.15 | 16.75 | 256.66 | -14.21 | 358.81 | 2.54 |
| 4.00 | 2.00 | 96.48 | 5.43 | 267.70 | -2.93 | 364.18 | 2.50 |
| 5.00 | 1.80 | 90.03 | 0.08 | 263.81 | -0.50 | 353.84 | -0.42 |
| 5.00 | 1.90 | 104.05 | 12.61 | 253.65 | -13.22 | 357.70 | -0.61 |
| 5.00 | 2.00 | 107.59 | 12.85 | 254.36 | -8.80 | 361.94 | 4.05 |
| 6.00 | 0.40 | 100.31 | 5.99 | 229.74 | 10.42 | 330.05 | 16.41 |
| 6.00 | 2.00 | 94.93 | 6.30 | 264.25 | -4.47 | 359.18 | 1.83 |
| 7.00 | 2.00 | 96.29 | 8.13 | 258.79 | -6.99 | 355.08 | 1.15 |

## C. Static Heterogeneous Market

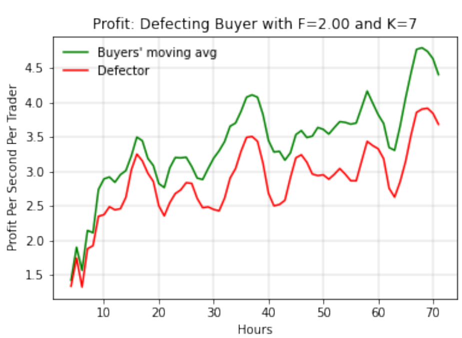
For the next sets of experiments, we bring in different types of traders into the market.

Drawing from experiments conducted by IBM [7], we introduce heterogeneity by conducting one-in-many experiments. However, if we were to try every combination of the 13 traders, this would require 288 experiments notwithstanding performing multiple trials to increase the validity of our analysis. As such, we take the original parameters in the Github implementation of PRDE [6] where K=4 and F=0.8 as the standard, and set each of the 13 traders as the defector, comparing the performance of these 13 traders to the standard. We repeat this for each trader taking turns to set the defector as either a buyer or seller. In this way, we decrease the number of experiments needed to run to 26.

By comparing the PPS per trader between the standard buyer and the defecting buyer, we see that the defector sometimes performs better, as illustrated in Figure 6a with F=2.0 and K=7. However, this is not always the case depending on the k and f values, as seen in Table IV, where the relative PPS decreases for certain combinations of k and F values. Compared to defecting sellers, buyers perform relatively worse. With the same values for k and F, we can see in 6b that the defector performs consistently worse than the standard throughout the market session. Table V also shows that for most defecting buyers, their PPS was lower than the average standard buyer. In the 2 cases that there was an increase in PPS, this difference was minuscule, suggesting that if a trader is acting as a buyer in a market filled with PRDE traders, the trader should follow the crowd and not defect.




(a) SMA PPS per trader of defecting seller




(b) SMA PPS per trader of defecting buyer

Fig. 6: Plot of SMA of PPS per trader for 3-day experiments averaged over 5 trials in a static market populated by 1 PRDE buyer/seller who has F=2.00 and K=4.0 and the rest of the traders with F=0.8 and K=4.0

TABLE IV: PPS per trader of the standard seller with K=4 and F=0.8 and defecting seller in a static heterogeneous environment

| k | f | Standard Seller PPS | Defector Seller PPS | Defector Profit Increase |
|---|---|---|---|---|
| 4.00 | 0.10 | 9.73 | 10.15 | 0.42 |
| 4.00 | 0.20 | 9.77 | 10.21 | 0.44 |
| 4.00 | 0.50 | 9.22 | 8.91 | -0.31 |
| 4.00 | 0.70 | 9.34 | 10.49 | 1.15 |
| 4.00 | 1.60 | 9.46 | 5.84 | -3.62 |
| 4.00 | 1.70 | 9.37 | 10.32 | 0.95 |
| 4.00 | 2.00 | 9.35 | 10.60 | 1.25 |
| 5.00 | 1.80 | 9.15 | 7.27 | -1.88 |
| 5.00 | 1.90 | 9.22 | 9.48 | 0.25 |
| 5.00 | 2.00 | 9.38 | 9.95 | 0.57 |
| 6.00 | 0.40 | 9.33 | 9.28 | -0.05 |
| 6.00 | 2.00 | 9.86 | 6.44 | -3.42 |
| 7.00 | 2.00 | 9.92 | 11.84 | 1.92 |

TABLE V: PPS per trader of the standard buyer with K=4 and F=0.8 and defecting seller in a static heterogeneous environment

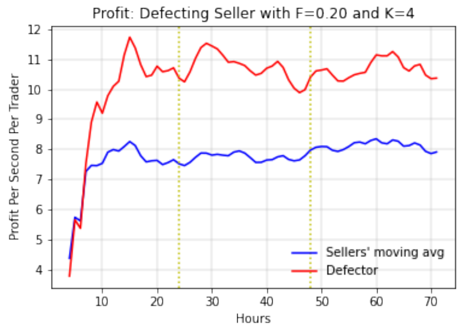
| k | f | Standard Buyer PPS | Defector Buyer PPS | Defector Profit Increase |
|---|---|---|---|---|
| 4.00 | 0.10 | 3.43 | 2.49 | -0.94 |
| 4.00 | 0.20 | 3.34 | 3.34 | 0.00 |
| 4.00 | 0.50 | 3.80 | 3.85 | 0.05 |
| 4.00 | 0.70 | 3.73 | 3.75 | 0.01 |
| 4.00 | 1.60 | 3.90 | 3.29 | -0.61 |
| 4.00 | 1.70 | 3.60 | 2.96 | -0.63 |
| 4.00 | 2.00 | 4.20 | 3.87 | -0.32 |
| 5.00 | 1.80 | 3.75 | 3.58 | -0.17 |
| 5.00 | 1.90 | 3.38 | 3.08 | -0.29 |
| 5.00 | 2.00 | 3.35 | 3.06 | -0.29 |
| 6.00 | 0.40 | 3.99 | 3.80 | -0.19 |
| 6.00 | 2.00 | 3.91 | 3.03 | -0.88 |
| 7.00 | 2.00 | 4.27 | 3.59 | -0.68 |

### *D. Dynamic Heterogeneous Market*

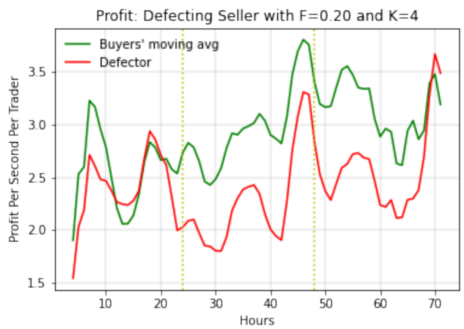
Repeating the methodology from section V-C and using the dynamic market setup from V-B, we perform the next set of experiments using one-in-many tests in a dynamic market. The trend of results are similar to that from V-C. Comparing table VI and VII, we can see that defecting buyers are mostly worse off, while sellers are usually better off defecting. This is illustrated in Figure 8, where the defector has K=4 and F=0.2: whereas the defecting seller has a consistently higher PPS compared to the standard seller, the defecting buyer has a lower PPS for the majority of the market session.

## VI. Statistical Tests

In order to confirm that the different traders comes from different populations and that the rankings are not due to stochasticity, we conduct series of Mann-Whitney U Test with an alpha value of 0.05. The null hypothesis assumes that the 2 populations are equal, and so if p-value $< 0.05$, we can reject the null hypothesis and conclude that the 2 populations of traders are not equal, and thereby rank them. However, after performing a series of statistical tests, I found that a lot of the




(a) SMA PPS per trader of defecting seller




(b) SMA PPS per trader of defecting buyer

Fig. 7: Plot of SMA of PPS per trader for 3-day experiments averaged over 5 trials in a dynamic market populated by 1 PRDE buyer/seller who has F=2.0 and K=7.0 and the rest of the traders with F=0.8 and K=4.0

TABLE VI: PPS per trader of the standard seller with K=4 and F=0.8 and defecting seller in a dynamic heterogeneous environment

| k | f | Standard Seller PPS | Defector Seller PPS | Defector Profit Increase |
|---|---|---|---|---|
| 44.00 | 0.10 | 9.25 | 10.55 | 1.31 |
| 4.00 | 0.20 | 9.63 | 12.80 | 3.17 |
| 4.00 | 0.50 | 9.34 | 11.38 | 2.05 |
| 4.00 | 0.70 | 9.12 | 8.36 | -0.76 |
| 4.00 | 1.60 | 9.40 | 11.57 | 2.17 |
| 4.00 | 1.70 | 9.35 | 7.29 | -2.05 |
| 4.00 | 2.00 | 9.04 | 11.28 | 2.24 |
| 5.00 | 1.80 | 9.03 | 10.53 | 1.50 |
| 5.00 | 1.90 | 9.13 | 9.66 | 0.53 |
| 5.00 | 2.00 | 9.37 | 12.46 | 3.09 |
| 6.00 | 0.40 | 9.17 | 11.45 | 2.27 |
| 6.00 | 2.00 | 8.77 | 7.75 | -1.03 |
| 7.00 | 2.00 | 9.09 | 10.39 | 1.30 |

p-values were higher than 0.05. For instance, when comparing the results of the top 2 ranked buyers in the homogeneous static, the p-value was 0.27.

## VII. Extending PRDE

There are different ways to mutate the population. The current implementation of PRDE uses the classic DE variant, referred to as 'DE/rand/1'. Using this scheme, the mutant

TABLE VII: PPS per trader of the standard seller with K=4 and F=0.8 and defecting seller in a dynamic heterogeneous environment

| k | f | Standard Buyer PPS | Defector Buyer PPS | Defector Profit Increase |
|---|---|---|---|---|
| 4.00 | 0.10 | 3.43 | 2.49 | -0.94 |
| 4.00 | 0.20 | 3.34 | 3.34 | 0.00 |
| 4.00 | 0.50 | 3.80 | 3.85 | 0.05 |
| 4.00 | 0.70 | 3.73 | 3.75 | 0.01 |
| 4.00 | 1.60 | 3.90 | 3.29 | -0.61 |
| 4.00 | 1.70 | 3.60 | 2.96 | -0.63 |
| 4.00 | 2.00 | 4.20 | 3.87 | -0.32 |
| 5.00 | 1.80 | 3.75 | 3.58 | -0.17 |
| 5.00 | 1.90 | 3.38 | 3.08 | -0.29 |
| 5.00 | 2.00 | 3.35 | 3.06 | -0.29 |
| 6.00 | 0.40 | 3.99 | 3.80 | -0.19 |
| 6.00 | 2.00 | 3.91 | 3.03 | -0.88 |
| 7.00 | 2.00 | 4.27 | 3.59 | -0.68 |

vector, v is calculated by $v_i = x_{r1} + F(x_{r2} - x_{r3})$. Here, we can see that the 'rand' indicates that the base vectors are randomly chosen. Another widely used mutation scheme is 'DE/best/1' [8], which is a more greedy version. Instead of randomly choosing the base vector, we select the current best vector in the population. The mutant vector is therefore calculated by $v_i = x_{best} + F(x_{r1} - x_{r2})$. We therefore use this extended version of PRDE to see how it performs compared to the original. We shall refer to this new PRDE trader as PRDE-best.

Static homogeneous experiments, as in section V-A are run for the PRDE-best traders but only with the top 4 performing traders, 2 each from the top 2 sellers and the top 2 buyers (section II).

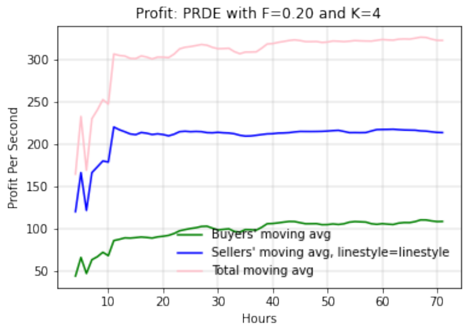
We can see the differences in PPS between PRDE and PRDE-best in table VIII. Although there was a slight increase of the PPS for 2 of the PRDE-best traders, there was also a significant decrease in PPS when k=4 and F=0.7. As such, more experiments will need to be conducted to gain a deeper insight into which mutation strategy is better.

TABLE VIII: PPS of PRDE-best compared with PRDE

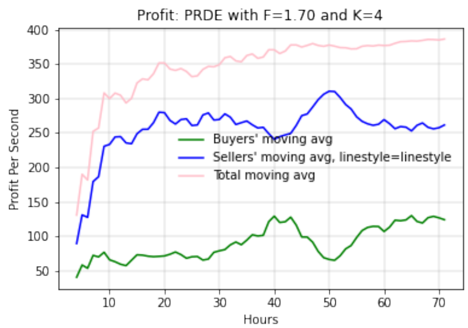
| k | F | PRDE-best Total PPS | PRDE Total PPS | Increase |
|---|---|---|---|---|
| 4.00 | 0.20 | 322.76 | 320.78 | 1.98 |
| 4.00 | 0.70 | 300.25 | 326.40 | -26.15 |
| 4.00 | 1.7 | 361.68 | 356.27 | 4.41 |
| 6.00 | 2.0 | 358.31 | 361.68 | -3.37 |

## VIII. Conclusion

A lot of market sessions were run across different sets of experiments. Different parameters performed better under different market condition. However, as discussed in section VI, we are unable to draw any concrete conclusions from our findings. Due to limited time, longer market sessions could not be run. Further experiments should therefore be conducted with longer trading windows and more trials in order to reduce the effect of stochasticity, and thereby hopefully, find valid results.




(a) SMA PPS using values of k and F from top PRDE buyer in a static homogeneous market




(b) SMA PPS using values of k and F from top PRDE seller in a static homogeneous market

Fig. 8: Plot of SMA of PPS for PRDE-best traders for 3-day experiments averaged over 5 trials in a static homogeneous market

However, our findings still shows that not 1 set of parameters stand out the different market environments, suggesting that perhaps one should choose which set of parameters to use depending on the situation of the market, e.g. if it is highly volatile or otherwise.

It should be noted that BSE is a simulation and therefore has a number of limitations compared to real world markets. For simplification, BSE assumes zero latency between traders and the exchange. However, in the real-world, trading companies take great pains to minimise this latency. Another simplifying assumption BSE makes is that the quantity of each trade is 1. Perhaps the only thing one can do to truly see how well algorithmic traders perform is to allow it to trade in a real trading market.

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