Evaluation of the Parameterized-Response Differential Evolution Trader-Agent

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***Abstract*—This paper evaluates the Paramaterized-Response Differential Evolution (PRDE) trader-agent.**

***Index Terms*—Automated Trading, Financial Markets, Adaptive Trader-Agents**

I. Introduction

Automated trading accounts for an unprecedented amount of activity in modern financial markets. These algorithms have the ability to execute trades at a frequency simply unachievable for humans beings; thus, the behaviour of many of these markets has fundamentally shifted. Notably, the 'flash crash' in US financial markets on 6 May 2010 has been partially attributed to high-frequency trading algorithms aggressively reselling short-term positions to one another. Many automated trading algorithms have the additional quality of being adaptive: they adjust their strategy to extract maximum profit from the market in which they are operating. Cliff [1] described these contemporary markets—in which competing adaptive algorithms are simultaneously engaged in coninual adjustment to maintain profitability—as co-evolutionary systems.

Large amounts of research has been conducted to understand the dynamics of these markets. Recently, Cliff introduced the Parameterized-Response Zero-Intelligence (PRZI) [2] trader: a nonadaptive generalisation of the ZIC [3] trader—the difference lies in the probability mass function (PMF) used to generate quote prices. Each individual ZIC trader samples their quote price from a fixed uniform distribution, whereas each PRZI trader is governed by a strategy parameter $s \in [-1, 1] \in \mathbb{R}$ that determines the PMF the trader samples from; the shape of this PMF determines how 'urgent' or 'relaxed' the trader acts. As $s \to 1$ the distribution is evermore biased towards 'urgent' quote prices—those closest to the least profitable price for the trader, but most likely to attract a willing counterparty—conversely, as $s \to -1$, the distribution is biased towards 'relaxed' quote prices—those that generate the most profit for the trader, but are considerably less likely to attract a counterparty. When $s = 0$, the PMF is uniform, identical to that of a ZIC trader.

PRZI Stochastic Hillclimber (PRSH) [4] is an extension to the PRZI automated-trader algorithm, also introduced by Cliff. The strategy parameter s is dynamically altered by the algorithm in an attempt to increase profitability. Each PRSH trader maintains a private local population $\mathcal{K}$ of k strategy parameters; each of which it evaluates for a specific period of time via a loop to identify which is most profitable. The most profitable strategy s_0 is 'mutated' $k-1$ times—these k values comprise the new elements of set $\mathcal{K}$.

PRZI Differential Evolution (PRDE) [1] is further extension of the PRZI algorithm, and a successor to PRSH; it is the most recent algorithm published by Cliff in the PRZI 'family' of trader-agents. It replaces the simple stochastic hill-climber with a differential evolution (DE) optimisation system [5]. Each PRDE trader maintains its own DE system with a population of candidate s-values of size $\mathrm{NP} \geq 4$, which for trader i can be denoted by $s_{i,1}, s_{i,2}, ..., s_{i,\mathrm{NP}}$. Once a particular strategy $s_{i,x}$ has been evaluated, three other distinct s-value are chosen at random from the population maintained by trader i: $s_{i,a}$, $s_{i,b}$ and $s_{i,c}$ such that $x \neq a \neq b \neq c$. A new candidate strategy $s_{i,y}$ is constructed as follows:

$$s_{i,y} = \max(\min(s_{i,a} + F_i(s_{i,b} - s_{i,c}), 1), -1)$$

where F_i is the trader's differential weight coefficient. This is very similar to the standard DE/rand/1 algorithm, with addition of $\max$ and $\min$ functions to constrain the output $s_{i,y} \in [-1, 1]$. The fitness of $s_{i,y}$ is evaluated and if it performs better than $s_{i,x}$ then $s_{i,y}$ replaces $s_{i,x}$; otherwise, it is discarded and then the next strategy is evaluated. Cliff made one additional modification to his implementation of DE/rand/1 algorithm in PRDE to deal with convergence issues that arised from $s_{i,b} - s_{i,c}$ tending very close to zero. He introduced a simple vector-perbutation mechanism: if at any time the standard deviation of the candidate s-values in trader i's private population is less than 0.0001, then a randomly selected candidate is provided a value drawn at random from the uniform distribution $U(-1, 1)$.

Cliff published experiments he ran on the *Bristol Stock Exchange* (BSE) (see [6], [7]) to analyse and evaluate PRSH and PRDE. BSE is a freely-available, open-source simulation a LOB-based financial exchange. Notably, Cliff identified that markets populated by PRDE traders were approximately 100% more economically efficient than those populated by PRSH traders [1]. However, the PRDE traders implemented in Cliff's experiments did not deviate from a differential weight of $F = 0.8$ and a number in population of $\mathrm{NP} = 4$ (i.e. the minimum viable value). He stressed the importance of future work to explore the effects on the market's dynamics of altering these key parameters.

II. Exploration of NP and F

In Cliff's paper introducing PRDE, he proposed two lines of future research regarding exploration of different values for the differential weight coefficient F and the number in population NP [1]. He proposed an exploration into the effects on the market's dynamics of altering the two key parameters homogenously—with all traders maintaining the same values of F and NP. He also proposed an arguably more intriguing exploration into effects that arise from altering the two key parameters heterogeneously—with different traders being provided different values of F and NP.

My initial experiments in this paper focus on the former exploration. To maintain consistency with Cliff, I also conducted my experiments on BSE, with a similar experimental setup. In each experiment, I implemented a homogenous population of 30 PRDE traders—15 buyers and 15 sellers—with identical values for F and NP. I used profit per unit time as a measure of market efficiency, namely profit per second (PPS).

III. Extending PRDE

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