The Performance of Option–Trading Software Agents: Initial Results

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Summary. We present a framework for intelligent software agents to manage risk and uncertainty in online marketplaces using Option Derivatives. To compare agents using Options with agents not using them, we create a simulation of a financial marketplace, in which software agents are vested with decision-rules for buying and selling goods and Options. We present some of the results of this simulation study.

1 Introduction

The growth of e-commerce and the development of distributed processing systems have led to interest among computer scientists in methods for resource allocations across multiple participants [3]. GRID systems, for example, allow multiple users access to some resource, such as computer processing power or use of an electron microscope [5].

If resources are limited, each agent in a GRID system or other online marketplace faces the possibility of not being able to obtain resources when needed. If resources are allocated according to a market mechanism (either with real-world money or with tokens), agents also face the possibility of not being able to afford to purchase resources, even when they are available. As computational resource allocation systems become increasingly common, participants will require agents able to reserve future resources on their behalf, and hedge against future risks.

Derivatives are financial products whose values depend on the value of some other asset, usually a physical product. Option derivatives provide traders with the right to purchase or the right to sell the underlying assets at agreed future times, under agreed conditions. In this way, traders attempt to hedge against falls in the price of the underlying asset or to gain from price rises, and so manage the risks associated with the uncertainty of asset prices.

Elsewhere, a multi–agent framework has been presented in which BDI–type agents could be vested with decision rules allowing them to trade some product [1]. We use this framework to create agents with similar decision rules for trading of option derivatives, and then undertake a Monte Carlo simulation to compare the marketplace performance of agents trading options with those which do not.

Our contribution comprises the results of the Monte Carlo simulation for which the paper concludes with a discussion of the work. It is important to stress that our focus throughout is not on the exchange mechanism by which agents trade options, or its properties; rather, our concern is with the relative benefits or disbenefits to agents undertaking Options trading.

2 Model Description

We created a multi agent market framework based on the model of [7]. In our model we consider *goods* instead of *stock*, the goods cannot be divided, we only consider one type of good or asset and the price of the asset is fixed from a external price series. In addition to the standard asset trading mechanism, our model provides means to exchange Option contracts among the agents. We make use of the basic properties of real financial Option contracts to define the Options that agents can trade. Price series of the underlying asset is set from an exogenous discrete time series and Option prices are calculated at each step using the Black-Scholes [2] model for Option pricing.

2.1 The Market

The market is composed of a set of agents $A = \{1, 2, 3..., N\}$. A_i is composed of two subsets of agents, agents that can trade options and goods A_o and agents that can only trade goods (assets) A_g.

We consider discrete time points $t = \{0, 1, 2, 3..., T\}$ and refer to a period of time as the tth period (or step t) $[t, t + 1]$. The market has also a risk free rate of return r.

At each t each agent i has a number of goods $g_i(t)$ and an amount of cash $c_i(t)$. The total number of goods in the model is fixed, being $\sum_i g_i(t) = G$ for all t. Each agent also has an Option portfolio $\mathcal{O}_i = O_i^w \cup O_i^h$ which is composed by the Options the agent holds (O^h) and the ones it wrote (O^w).

An Option α is defined as:

$$\alpha = \langle X^\alpha, t^\alpha, v^\alpha, \tau^\alpha \rangle \tag{1}$$

Where X^α is the exercise price of that Option (the price agreed to pay for each good); t^α is the expiration time; v^α is the volume (the quantity of goods to trade with that Option) and τ^α is the type of Option (call or put). Each Option α has a corresponding premium price p_α(t). This is the price an agent will have to pay its counter–party to hold the Option.

The Options provided by the market are a set of standard *templates* for Option contracts that the agents can trade. Agents are only allowed to exchange Options that comply with the specified templates, this is similar to a real Option regulated market. The number of available Option templates is constant over all time steps.

Pricing Mechanism

The asset price $p(t)$ will be provided to the model from an external time series. Option pricing is calculated each step using the Black-Scholes model for Option pricing defined in [2][1]. Using this model, the price of an Option is calculated from the price of the good $p(t)$, the variance of the asset price (σ) and a predefined exercise price X^α. The exercise price of an Option is obtained by the following formula:

$$X^\alpha = p(t) \times (1 + k)$$

Where k is a uniformly distributed pseudorandom number within the range $[-SP_k, SP_k]$.

Market Timeline

Each period of time starts when the market *publishes* the new price for the asset. After obtaining this price the *Option clearing* phase will run where the market will receive instructions from the agents to exercise any Option that expires at this time. The agents holding any expiring Option must either decide to exercise or lose the Option at

[1] It is worth noting that other Option pricing mechanisms could hahe been used, in fact some experiments were also ran using the Binomial Option Pricing model [4] without any relevant difference in the outcomes.

this time. Any non exercised Option should be removed from agent's held Options set O_i^h. Any request to exercise an already expired Option will be ignored by the market. In the event of an Option being exercised, the agents will clear the Option, trading the corresponding asset immediately.
Afterwards, the market will publish the different Option templates to trade on that period and the *trading phase* will start where the agents will submit their offers to buy and sell assets or hold and write Options. Next, the market will try to match match randomly the asset buy and sell offers and will also try to match the hold and write offers. Finally, the market will clear the matched offers by making the agents exchange the assets or confirming the matched Option contracts. A graphical representation of the timeline is shown in Figure 1.

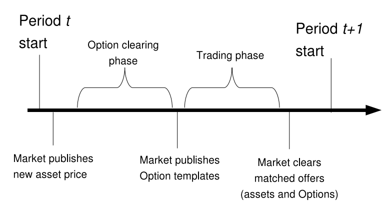

Fig. 1. Timeline for one time step of the market

2.2 Trading Agents

An agent i is defined by the tuple:

$$\langle g_i, c_i, w_i, \mathcal{O}_i, \mathcal{S}_i, \mathcal{F}_i \rangle \tag{2}$$

At time t, the term $g_i(t)$ is the number of goods the agent owns at time t; $c_i(t)$ denotes the quantity of cash the agent has. The term $w(t)$ denotes the *wealth* of the agent which is obtained by the equation:

$$w(t) = p(t) \times g(t) + c(t) \tag{3}$$

The agent also owns a set of Option contracts $\mathcal{O}$ which represent a contract to buy or sell one asset at a specific time. The set of Options is composed by two subsets, O^α is the set containing the held Options and O^β contains the Options written. Specifically $\mathcal{O} = O^\alpha \cup O^\beta$.
The term $\mathcal{S}$ is the agent's strategy (See 2.4) comprising an action or chain of actions to execute. The set of actions an agent can execute are listed in Table 1. Finally, $\mathcal{F}_i$ is the forecast strategy used by the agent.

Action	Description
$buy(g,t)$	Make an offer to buy an asset at time t.
$sell(g,t)$	Make an offer to sell an asset at time t
$hold(\alpha,t)$	Make an offer to hold Option α at time t
$write(\alpha,t)$	Make an offer to write an Option at time t

Table 1. Available actions for the agents at time t.

2.3 Forecasting and perceived Risk

The forecasting process of the agent is comprised by two parts, firstly the agent obtains forecasted price of the asset for future time steps and secondly it uses these forecasts to obtain its perceived risk of executing the possible actions. At each time step agents calculate a forecasted price for future time steps. Agents obtain this price using a forecasting function. Although other types of time series forecasting formulae could be used, our model implements two forecasting mechanisms.

Simple Moving Average Forecasting

The first forecasting mechanism is based on the Simple Moving Average (SMA). Prices at future times are obtained by first calculating the SMA for the interval $[t-n,t]$ as $p_{SMA}(t)$ and then the price at future time steps is obtained by extrapolating the price at current time using the formula:

$$p_i(t+m) = p(t) + m \times (p(t) - p_{SMA}(t)) \tag{4}$$

Where $p_i(t+m)$ is the agent's forecasted price for time $t+m$ and $p(t)$ is the market price at time t.

α–Perfect Forecasting

Using the second forecasting mechanism called the α–perfect forecast the agent will obtain the future prices from the real time series with some added random variability (noise). The forecasted price will be calculated as:

$$p_i(t+m) = p(t+m) \times (1 + r_\alpha) \tag{5}$$

Where $p_i(t+m)$ is the agent's forecasted price at $t+m$, $p(t+m)$ is the real market asset price at time $t+m$ and r_α is a uniformly distributed pseudo–random number within the range $[1-\alpha, \alpha-1]$, being α within the range of $[0,1]$. Using this mechanism, it is possible for the agent to have complete knowledge of the future prices when α equals 0.

Perceived Risk

Inspired by [6], we model risk as the probability that the agent loses wealth when it carries out a specific action. We assume prices are distributed Normally. Under this assumption each agent can calculate the probability of wealth loss $\rho(a)$ for each possible action a at each step in time t.
This is achieved by using the cumulative standard normal distribution to obtain the cumulative probability of the agent forecasted price being in the wrong direction, assuming that the distribution's mean is $p_i(t+m)$ (the price at the forecasted time step).

2.4 Trading Strategies

There are two types of agents trading in the market, asset traders and Option traders; asset traders can only trade the underlying asset in the market whereas Option traders can trade assets and Option contracts.

Asset Trading Strategies

Asset traders trade in the market using one of two strategies: the Random trading strategy in which the agents select an action randomly and Speculator strategy in which agents select an action to buy or sell an asset according to their forecast of the price at the next step.

Option Trading Strategies

Option traders can trade using the *Minimise Risk* strategy in which agents create an action tree with all the possible combinations of actions for a specific number of time steps and select the path which yields the minimum combined risk. An agent that uses this strategy will choose the sequence of actions from the action tree (a path) where the combination of the actions' risk loss factor ρ is the minimum from all possible combinations. Let a strategy S be defined by the sequence of actions $\langle a_1, a_2, ...a_n \rangle$ and also let $\rho(a_i)$ be the risk loss factor for doing some action, the combined risk loss $\rho_s(S)$ for such strategy is defined as:

$$\rho_s(S) = \prod_{i}^{n} \rho(a_i) \tag{6}$$

Option trading agents can also use the *Maximise wealth* strategy with which they select the next action after selecting the path which yields the maximum sum of wealth from an action tree. An agent that uses this strategy will choose the sequence of action from the action tree where the combination of each of the action's wealth difference is the maximum from all possible combinations. Let a strategy S be defined by the sequence of actions $\langle a_1, a_2, ...a_n \rangle$ and let $\Delta w(a_i)$ be the perceived wealth difference for doing an action (the wealth before executing the action substracted from the wealth after executing the action), the combined wealth $\Delta w(S)$ is defined as:

$$\Delta w(S) = \sum_{i}^{n} \Delta w(a_i) \tag{7}$$

3 Experiments

Several experiments were run to compare the performance of agents under two different aspects. Firstly to test which of the strategies generated higher profits and secondly to compare the correlation between the agents' wealth and the price of the asset. Our hypothesis was that, the wealth of agents using Options would be lower than that of the ones trading only assets.

3.1 Environment Setup

A simulation run for our model requires the specification of the parameters of Table 2 for the market setup and for the agents.The parameters are explained in Section 2 excepting O_s which is used to set the distance between the expiration time (t^{α}) of the Options generated at each step and $\sigma(0)$ which is the initial value for the standard deviation of the price series. These parameters were fixed for all the experiments.
For all the experiments we also populated the market with 4 sets of 20 agents. All agents within one set were initialized with the same parameters (including strategy and forecast function). Each set used one of the four defined strategies. All the experiment were done using each of the price series to be described.

Price Series

To set the price of the underlying asset we used several price series in order to test the performance of the agents under different market conditions. We defined three categories for the price series: stock prices series, which were obtained from the closing prices of different stocks

Initial parameters for the market	
Parameter	Initial value
Simulation duration (T)	500
Number of available Option templates ($\|O\|$)	3
Steps between available Options (O_s)	1
Strike Price multiplier (SP_k)	15
Risk free rate (r)	0.005
Initial price variance ($\sigma(0)$)	1
Initial parametrs for agents	
Parameter	Initial value
Initial cash ($c_i(0)$)	1000
Initial goods ($g_i(0)$)	100

Table 2. Initial parameters for the experiments

[2]; random prices, which are uniformly distributed pseudo–randomly generated series; and linear prices which are manually generated.
Some statistical information for the price series is summarized in Table 3. The Dell, Microsoft, HP, and IBM price series were obtained from the stock prices of the corresponding companies; the RANDOM1 and RANDOM2 price are the pseudo–randomly generated; finally, the Increment price series was generated as a constantly increasing time series and the Decrement was generated as a constantly decreasing time series.

	N	Minimum	Maximum	Mean	Std. Deviation
DELL	500	16.15	30.63	25.78	2.44
HP	500	10.75	37.80	21.46	6.34
IBM	500	54.65	125.00	95.66	17.37
MICORSOFT	502	41.75	73.70	58.43	7.40
RANDOM1	500	1.20	200.00	103.18	58.30
RANDOM2	500	4.00	996.80	501.54	293.44
INCREMENT	500	10.00	510.00	260.00	144.77
DECREMENT	500	10.00	509.00	259.50	144.48

Table 3. Descriptive statistics of the used price series

3.2 Experiments Using SMA Forecasting

For the experiments with the Simple Moving Average forecasting, all the agents were assigned this same forecasting function ($\mathcal{F}_i$) with the number of periods $t_{\mathcal{F}_i} = 10$. We ran 50 repetitions of each experiment

[2] Freely available online at http://finance.yahoo.com/

and averaged the results. We also calculated the mean of the wealth for each set of agents to obtain the performance for each strategy.

Performance of Strategies

We measured the performance of each strategy by obtaining the difference between the wealth of the agent at the last time step and the first time step, this resulted in the profits that each agent obtained for each simulation (see Table 4). In order to compare the profits among

	Opton Traders		Asset Traders		
	MinRisk	MaxWealth	Speculator	Random	Mean
DELL	210.890	-171.660	-74.060	34.830	960.000
IBM	-177.342	45.537	-9.782	141.587	-558.827
HP	-363.480	292.750	38.980	31.750	-1393.000
MICROSOFT	-3.892	-1.262	-39.422	44.578	817.003
RANDOM1	-259.283	265.357	-2384.593	2378.518	-11979.998
RANDOM2	2373.450	-946.150	-21119.950	19692.650	51073.250
INCREMENT	9922.925	-8430.975	8441.825	-9933.775	49899.975
DECREMENT	-3547.801	-2561.132	509.389	5599.545	-47310.719

Table 4. Average profit for each strategy with SMA forecasting.

the agents we calculated the mean of the average profits (last column in Table 4) and subtracted it from the strategy profit. Figure 2 shows the relative profits for each strategy among the simulations; from this figure it can be seen that there is no clear advantage in the profits using any strategy.

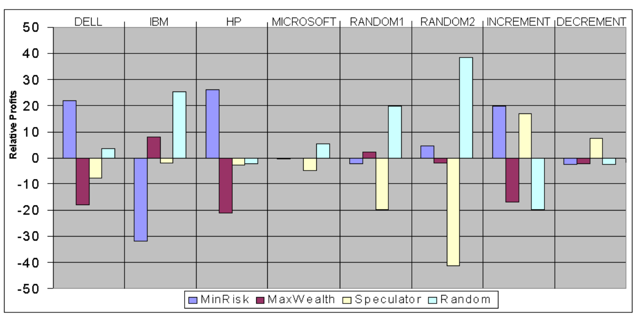

Fig. 2. Relative profit for each strategy with SMA forecasting

Performance Correlation with Price

The second test we performed was an analysis correlation between the price series and the wealth of the agents. This test was conducted to see whether the fluctuations on the price of the asset had less incidence in the wealth of an agent trading Options, the results[3] on Table 5 suggest so, as the correlation between the wealth of the Option trading strategies is slightly less than of the asset trading strategies for three of the four stock market strategies.

	Opton Traders		Asset Traders	
	MinRisk	MaxWealth	Speculator	Z.I.
DELL	0.994	0.974	0.998	0.999
HP	0.999	0.997	1.000	1.000
IBM	1.000	1.000	1.000	1.000
MICROSOFT	0.999	0.999	1.000	1.000
RANDOM1	0.999	1.000	0.970	0.985
RANDOM2	1.000	1.000	0.982	0.990
INCREMENT	1.000	1.000	1.000	1.000
DECREMENT	1.000	1.000	1.000	1.000

Table 5. Correlation between agents' wealth and price series with SMA.

3.3 Experiments using α–Perfect Forecasting

For the experiments with the α–Perfect forecasting function, all the agents were assigned this forecasting function ($\mathcal{F}_i$) with three different α values of 10, 20 and 40. We ran 50 repetitions of each experiment and averaged the results. We also calculated the mean of the wealth for each set of agents to obtain the performance for each strategy.

Strategies Performance

As with the SMA experiments, the performance of each strategy was measured by obtaining the difference between the wealth of the agent at the last time step and the first time step, resulting in the profits that each agent obtained for each simulation. Figures 3 shows the resulting relative profit for each strategy with the different α values.
The wide difference in the performance of the Option trading strategies against the asset trading strategies suggests a clear advantage on the use of Options in the case of the α–Perfect forecasting.

[3] All correlations were calculated as two tailed Pearson correlation significant to the 0.01 level.

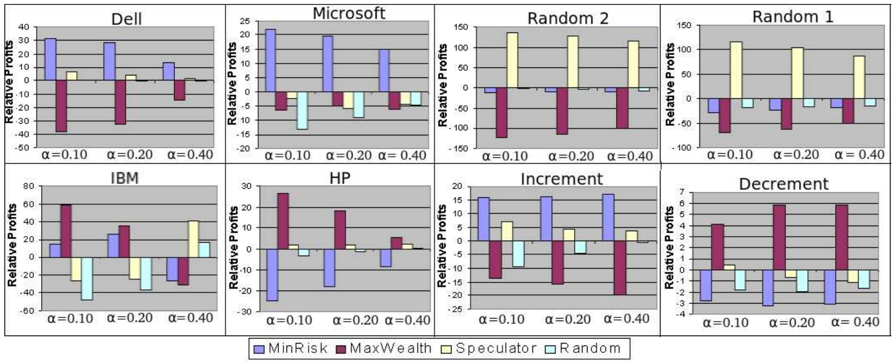

Fig. 3. Relative profit for each strategy with α–Perfect forecasting with different α values.

Performance Correlation with Price

Finally, the correlation between the price series and the wealth of the agents was calculated for the α–Perfect experiments. The results of this are listed on Table 6, the lower correlation of the Option Trading strategies particularly appear to indicate that the use of Options decreases the influence of the price in the wealth of the agents trading them.

Correlation for $\alpha = 0.10$				
	Opton Traders		Asset Traders	
	MinRisk	MaxWealth	Speculator	Random.
DELL	0.988	0.831	0.998	0.999
HP	0.999	0.993	1.000	1.000
IBM	0.999	0.997	1.000	1.000
MICROSOFT	0.997	0.992	1.000	0.999
RANDOM1	0.999	0.718	0.841	1.000
RANDOM2	0.999	0.718	0.841	1.000
INCREMENT	1.000	1.000	1.000	1.000
DECREMENT	1.000	1.000	1.000	1.000

Correlation for $\alpha = 0.20$				
	Opton Traders		Asset Traders	
	MinRisk	MaxWealth	Speculator	Random.
DELL	0.984	0.884	0.999	1.000
HP	0.998	0.991	1.000	1.000
IBM	0.999	0.997	1.000	1.000
MICROSOFT	0.997	0.992	1.000	1.000
RANDOM1	0.999	0.761	0.861	1.000
RANDOM2	0.999	0.765	0.879	1.000
INCREMENT	1.000	1.000	1.000	1.000
DECREMENT	1.000	1.000	1.000	1.000

Correlation for $\alpha = 0.40$				
	Opton Traders		Asset Traders	
	MinRisk	MaxWealth	Speculator	Random.
DELL	0.994	0.985	0.998	1.000
HP	0.997	0.992	1.000	1.000
IBM	1.000	0.999	1.000	1.000
MICROSOFT	0.998	0.998	1.000	1.000
RANDOM1	1.000	0.833	0.889	1.000
RANDOM2	0.999	0.833	0.904	1.000
INCREMENT	1.000	0.999	1.000	1.000
DECREMENT	1.000	1.000	1.000	1.000

Table 6. Correlation between agents' wealth and price series with α–Perfect forecasting.

4 Conclusions

In this paper we demonstrated some of the results from the experiments performed in our proposed Option Market framework. The experiments so far show promising results. It is worth nothing that, although the differences in the results of the tests between Option traders and asset traders are low, we argue that the reason for this could be due to the simplicity of the market. Allowing the agents to trade more than one asset at each step in time and providing them with Options with a higher volume (more than one asset traded on each Option) might increase the differences among the agent's performance. Also, it would be interesting to introduce the concept of *magnitude* of risk into the agents reasoning process.

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