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A Two-Level Cascade Evolutionary Computation Based Covered Call Trading Model

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Abstract

In this study, a two-level cascade stock trading model is proposed. In the first level, the buy/sell signals are created by optimizing the RSI technical indicator parameters with evolutionary computation techniques. Then using the selected parameters, in the second level actual trading is performed using an optimized covered call strategy. Again, the optimization is implemented with evolutionary computation. In this particular study, genetic algorithms (GA) and Particle Swarm Optimization (PSO) are chosen as the soft computing methods for optimization. Historical end-of-day close values and options data for the S&P 500 Spider ETF (SPY) and 4 other ETFs (EWZ, XLE, IWM, XLF) between years 2005-2009 are used. The system is trained using the data between 2005 and 2008; the testing is done with 2009 data. The results indicate that the proposed model outperformed not only the buy and hold strategy, but also buying and selling the ETF alone without the options. In future work different stock/ETF data and different combined options strategies will be included in the model to identify performances of different techniques.

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Keywords: Stock trading; technical analysis; RSI; options trading; covered call; genetic algorithms (GA); particle swarm optimization (PSO); evolutionary computation

1. Introduction

Soft computing methods have been used for stock market forecasting and creating successful trading strategies for quite some time now [6]. However with the availability of more financial instruments, such as derivatives (options, futures, etc.) to the online trading platforms, individuals, in addition to market professionals, is now also able to implement complex trading strategies. Even though these new instruments can be used for leverage and/or hedging for portfolio risk reduction, it also brings additional complexity into the strategy development problem.

In this study, a complex trading model using an optimized covered call strategy is attempted. The model consists of two-levels; in the first one when to buy and sell is decided, i.e. the buy/sell signal trigger points are calculated by

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GA and PSO. In the second level, the call option part of the covered call strategy is optimized such that the best option is selected for profit maximization. In Section 2 and 3, GA and PSO are briefly introduced respectively. Section 4 describes the proposed model, results are in Section 5, conclusions and discussions follow in Section 6.

2. Genetic Algorithm (GA)

Genetic algorithm is a very popular method among evolutionary algorithms. This algorithm represents solutions as chromosomes and solution parameters as genes. Every chromosome is a candidate solution for the problem in the search space. The group of chromosomes is called population. A chromosome's quality is evaluated by a fitness function. The best chromosome in the population is the one that makes the result of the fitness function minimum or maximum, depending on the problem. To obtain the best chromosome, the algorithm produces new generations from current chromosomes. In every generation, natural evolution methods are performed on the starter (parent) chromosomes and child chromosomes are obtained. Evolution methods are *selection* (selecting chromosomes as parents from current population), *cross-over* (obtaining a new chromosome from two parent chromosomes) and *mutation* (randomly changing some genes on a chromosome).

Evolution methods are used for producing new solutions and overcoming the local maximum problem. Cross-over provides producing a new candidate solution by combining genes of its parents. To improve the parent selection process, our algorithm uses elitism rate which means the best chromosomes are transferred to the next generation unchanged, so the quality of population and probability of creating better generations are improved. Mutation, randomly changes a gene's value to overcome the local maximum problem. Random changes on the chromosomes may result in producing better solutions. Mutation rate is generally a small number because when selected high, the algorithm becomes a random search. The details of how genetic algorithm runs can be seen in [5].

The size of a population is another important factor, as possibility of finding a feasible solution earlier increases with the population size. On the other hand, algorithm gets slower when the population size increases; in this study a population size of 1000 is chosen. Elitism rate is selected as 0.01, which means in every iteration, 1 percent of the best chromosomes will stay unchanged. In this study mutation rate is selected as 0.05.

In this study, genetic algorithm is used for optimizing the RSI indicator parameters and option trade parameters. At the same time, another evolutionary algorithm, Particle Swarm Optimization (PSO) was also implemented in parallel and the performance results are compared.

3. Particle Swarm Optimization (PSO)

PSO is an optimization technique first introduced by Kennedy and Eberhart in 1995[1]. This optimization technique was inspired by the movements of birds, how they were gathered in one place. PSO technique is recently used in financial optimization problems like portfolio optimization [2] and option pricing [3]. In this study we used PSO to optimize the parameters for making profit with option trade, and compared the results with the GA's results.

In Particle Swarm, the particles are candidate solutions and the swarm represents all possible solutions. All particles or candidate solutions have a position ($\mathbf{x_i}$), velocity($\boldsymbol{\upsilon_i}$) and a best position($\mathbf{p_i}$). These values are vectors, including real numbers. In position vectors, the values are parameters, and velocity vector holds the information about how it can move in the search space. The position which makes the cost function minimum is the best position of the particle. The parameter number equals the vector size. All the values have bounds that change depending on the problem and the parameters. Also, there is a cost function which is used for deciding how well the solution is. This algorithm aims to minimize the cost function.

Particle's movement in the search space is calculated from the formulas 1 and 2. $\boldsymbol{\omega}$ is the inertia weight which usually has the value 1 or 0.9. A particle's speeding value is given by $\boldsymbol{\alpha}$ parameters. If speeding values are given high, then particles' position will be very different. This may cause a jump over an efficient solution. On the other hand, if values are selected as small numbers, then particles will not move far enough from their position and search time will be longer. In this study, $\boldsymbol{\alpha}$ values are selected as 2.

$$\upsilon_i = \omega\upsilon_i + \alpha r(p_i - x_i) + \alpha r(g - x_i) \tag{1}$$

$$x_i = x_i + \upsilon_i \tag{2}$$

To implement PSO, first, all particles are initialized with uniformly distributed random position values in the bounds and the swarm position is one of the particle's best positions that make the cost function value minimum. Then, to avoid local minimum and be able to find the global minimum of the cost function, the velocity vector is used. With randomized velocity for each dimension or parameter, particles are able to move around the search space. Until a result criterion is found, the velocity vector is updated with random numbers and added to the position vector for each particle. If the new vector's position cost is less than the particle's best position cost, the particle's best position is updated with the new vector. Also, if the new vector's cost is better than the swarm position cost, than swarm position is updated, too.

Particle swarm always searches for a better solution. It generates randomized particles with position and velocity vectors and updates its values when a better solution according to cost function is found. When the algorithm comes to an end, the final swarm position value is the best position for the entire swarm.

In our study, we are trying to calculate the profit with parameters in the swarm position vector. Particle swarm algorithm tries to make the cost function minimum and we want to achieve the maximum profit. In this case, we changed our cost function for returning the negative value of the profit to make it a minimum.

4. Proposed Model

In this section, the details about the proposed model are provided. First, the option selection process is described. Then, a brief introduction is given for the RSI indicator that is used as the buy/sell indicator for the overall system along with the explanation about the RSI indicator optimization. In the second level, the covered call strategy is developed by selecting the appropriate strike price and expiration date for optimum trading performance. Also, a brief introduction to covered call strategy is provided. Finally, the optimization in the second level was explained.

4.1. Option Group Model

For a particular stock/ETF, its option data is very large, so finding an appropriate option might take a long time. We used a new model for storing options to decrease the search time. A valid option on a certain day is an option which has not yet been expired and has already appeared on that day. In our study, options are grouped by their expiration dates as *Option Group Holders* in the first step, then their appearance date as *Option Groups* in option group holders. Options stored in the option groups are separated by their types as *Puts* and *Calls* (Figure 1).

Every ETF has their own list of option group holders and option group holders have lists of option groups. Option group holders and Option Groups are ordered by expiration date and appearance date. When searching for an option of an ETF on a particular day, the option group holder and its option group is found using binary search; reducing the time complexity to O (logn) for finding an option's group. After finding the option group, an appropriate option is searched by its type and its strike price value. If an option with given parameters does not exist, the closest one is selected. If expiration date is not found on the list, then the nearest expiration date is selected.

4.2. RSI Indicator

RSI is among the most common technical analysis indicators used in trading systems. Traders use RSI to identify the overbought and oversold conditions of the stock/ETF. The parameters of the RSI indicator are the RSI period and the overbought, oversold threshold levels. 14 day RSI and 30-70 RSI levels are the most commonly preferred values. Detailed description of the RSI indicator and other technical analysis indicators can be found in [7].

In this study, RSI parameters are optimized using GA and PSO. The chromosome structure is consisted of the buy period, buy level, sell period and the sell level. Different values are used for uptrend and downtrend cases.

4.3. Covered call strategy

Options are derivative products which gives the owner the right to buy or sell a stock/ETF on a pre-specified strike price until its “expiration” date. In contrast to future contracts, options do not have to be used. Options which gives the right to buy the corresponding stock at a given strike price are *call options.*

Covered call strategy suggests buying a stock/ETF and selling its call option at the same time on the buy signal and selling the stock/ETF and buying its call option on the sell signal. This reduces the loss when stock/ETF value is decreased because option becomes worthless and its initial selling price is our profit. On the other hand, if stock/ETF value increases, option will be used and profit will be limited. Figure 2 illustrates how our profit changes by stock's strike price. More explanation about covered call and other option strategies can be found in [8].

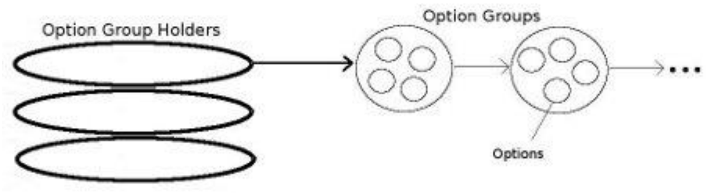

Fig.1. Option Group Holder Model

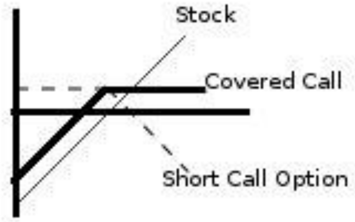

Fig.2. Covered Call

4.4. Two-level cascade model

In our study, we used a two-step strategy (see Figure 3). First step was to find the optimized values of RSI indicator with evolutionary algorithms for an ETF trade. At the second step, with these determined values from the first level, the program produces buy and sell signals to trade ETF and its options and optimizes option's strike (strike) value and the number of days between the transaction date and the option's expiration date (difference).

For the RSI indicator, we need a period of days and a threshold value as parameters to produce a signal. To buy and sell, RSI parameters will be different so we make four parameters as buy-period, buy-threshold, sell-period and sell-threshold. To improve the results, we decided to use different parameters for upward and downward trends. Trends are decided by calculating Simple Moving Average (SMA) for different days [4]. In this study SMA(50) and SMA(200) are used to decide trends. If SMA(50) crosses upward SMA(200), it means the trend is upwards, since the short term average is higher than the long term average. In the opposite case, short term average is lower than long term average, it means the trend is downwards. Since upward and downward trends are considered in this study, we use different parameters for upward and downward trends and have a total of 8 parameters.

In the second level, the most profitable covered call option is selected with the given buy/sell points obtained in the first level with the RSI optimization. In this case, the option parameters to be optimized are the strike price of the option (actually the percent difference of the strike price and current ETF price) and the time length of the option.

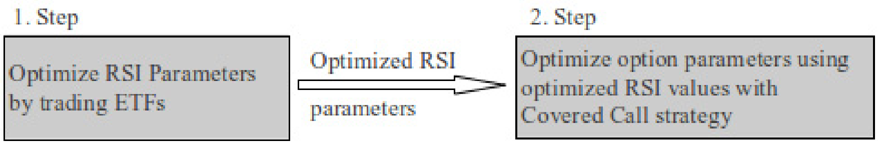

Figure 3. Flow chart of Two-level cascade model

5. Results

With GA and PSO, 8 RSI indicator parameters are optimized in the first level, and the results for SPY ETF are shown in Table 1. For 5 different ETFs, the model performance is compared to ETF buy strategy with optimized RSI and Buy & Hold (Table 2). Parameters found in the first step are used to trade the ETFs and its options for the covered call strategy. GA and PSO are used to train option's difference and strike values. For GA, the difference is found as 10 and the strike is -9.91, which means the option that will expire in 10 days with the strike price that is %9.91 less than the current price is chosen. For PSO, the difference is found as 11 and the strike is -9.27.

Table 1. RSI parameter values found by GA for SPY

An example of a column heading	GA	PSO
Downtrend RSI Buy Period	7	6
Downtrend RSI Buy Threshold	29.1	2.25
Downtrend RSI Sell Period	5	5
Downtrend RSI Sell Threshold	76.85	79.07
Uptrend RSI Buy Period	19	4
Uptrend RSI Buy Threshold	23.79	25.39
Uptrend RSI Sell Period	19	11
Uptrend RSI Sell Threshold	81.88	72.13

Table 2. Performance comparison of B&H, ETF buy and the proposed model

		GA		PSO	
	Buy & Hold	ETF buy with Optimized RSI	**Covered Call**	ETF buy with Optimized RSI	**Covered Call**
SPY	22.80	10.31	**20.80**	16.85	**13.19**
XLE	13.30	19.99	**69.61**	22.18	**57.77**
XLF	18.30	-0.83	**7.91**	10.45	**14.38**
EWZ	103.98	82.20	**220.83**	82.28	**221.72**
IWM	25.52	23.25	**34.23**	19.40	**5.06**

The corresponding transactions and trade performances for 3 ETFs (SPY, EWZ and XLE) are shown in Table 3. The training and test results for different algorithms i.e. annual profits, transaction count, positive transaction rate, average profit per transaction and average trade period (time between buy and sell) are shown in this table.

Table 3. Trading Performance Results of GA and PSO (P. = Profit (%), T.T. = Total Number of Transactions, A.T.Y. = Average Transaction per Year, P.T.R. = Positive (Successful) Transaction Rate (%), A.P.T. = Average Profit per Transaction (%), A.T.P. = Average Trade Period in days, PDD = Portfolio Drawdown, TDD = Transaction drawdown, T.P. = Transaction Profit (%), P.V. = Portfolio Value)

	SPY				EWZ				XLE			
	G.A.		P.S.O.		G.A.		P.S.O.		G.A.		P.S.O.	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
Total P.	302.30	20.80	1152.23	13.19	1082.07	220.83	953.39	221.72	441.05	69.61	876.19	57.77
Annual P.	41.69	20.80	88.61	13.19	85.58	220.83	80.30	221.72	52.60	69.61	77.18	57.77
T.T.	21	4	37	8	11	5	10	5	20	5	22	8
A.T.Y.	5.25	4	9.25	8	2.75	5	2.5	5	5	5	5.5	8
P.T.R.	66.67	100	54.05	25	81.82	80	80	80	70	80	81.82	75
A.P.T.	7	4.69	6.70	1.46	20.69	21.38	21.98	22.06	8.43	11.15	9.54	5.41
A.T.P.	20.81	25	18.65	16.13	47.73	39.80	56.10	40	45.85	44.40	43.23	31.38
MaxTDD	-0.38	0.67	-0.56	-1.33	-1.55	-0.32	-1.55	-0.33	-0.94	-1.23	-0.89	-1.24
Max T.P.	18.82	9.68	18.53	8.11	40.96	46.33	40.96	46.13	23.25	26.78	24.98	11.98
MaxPDD	100000	100000	100000	96358	100000	100000	100000	100000	98769	100000	100000	100000
Max. P.V.	402296	120796	1252228	113190	974453	280463	867947	280688	544263	172361	832936	157773

Figures 4 and 5 show the trade performance and the capital appreciation graph of the two-level model for SPY when the first level (RSI) and the second level (covered call selection) are optimized using GA and PSO, respectively. (the trade performance and portfolio statistics are presented in Table 3)

6. Conclusions and Discussions

A two-level Covered Call strategy with GA and PSO is proposed. Both levels are optimized separately and the results indicate that the trading optimization provided better results when compared to single stock trading and Buy & Hold (Table 2). 5 different ETFs are tested using both GA and PSO. Optimized RSI combined with covered call strategy, the proposed model, shows better results compared with Buy & Hold for both GA and PSO. Also when these results are compared with a previous similar study [6], GA and PSO showed superior results (around %80 of the transactions were successful) compared to any method that was mentioned in that study. Figures 4 and 5 and Table 3 indicate the model provided relatively consistent and robust buy/sell decisions even when it is used for different ETFs. With this particular option strategy, the time decay of the option premium is used for increasing the profit. This worked well in our study, since the average transaction period is within the range of 20-50 days, selling short dated options boosted the transaction profits. In future work, trend detection can also be included in the optimization as the initial level, also different indicators and option strategies can be included into such model.

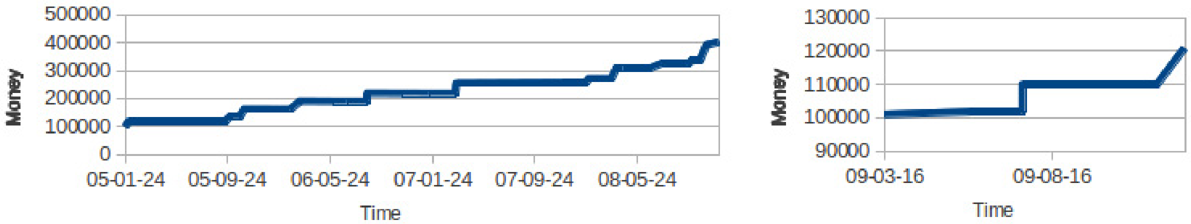

Fig.4. The Covered Call trading performance using the GA optimized RSI parameter values (a) for training period, (b) for testing period. . (x axis shows the time period in year-month-day format, y axis indicates portfolio value in dollars, beginning portfolio is 100K dollars)

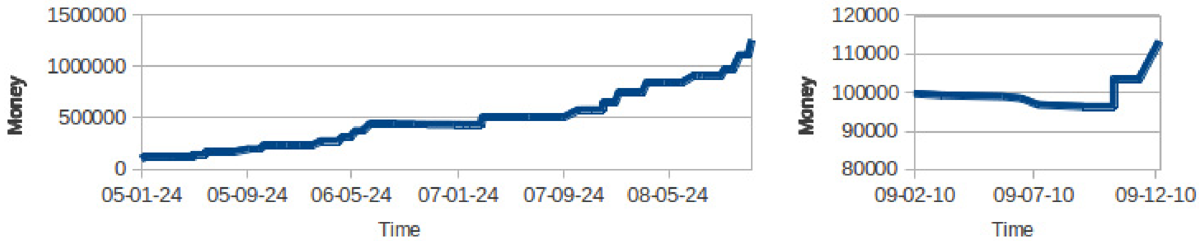

Fig.5. The Covered Call trading performance using the PSO optimized RSI parameter values (a) for training period, (b) for testing period. (x axis shows the time period in year-month-day format, y axis indicates portfolio value in dollars, beginning portfolio is 100K dollars)

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