Developing a Two Level Options Trading Strategy Based on Option Pair Optimization of Spread Strategies with Evolutionary Algorithms

Ilknur Ucar*, Ahmet Murat Ozbayoglu †, Mustafa Ucar‡
*† ‡TOBB University of Economics
and Technology, Ankara, Turkey
*ibayram@etu.edu.tr, †mozbayoglu@etu.edu.tr, ‡mucar@etu.edu.tr

***Abstract*—In this study, a two level options trading strategy is modelled and optimized with Genetic Algorithms and Particle Swarm Optimization for profit maximization. In the first level, the trend is found and in the second level, options trading strategies for the particular trend are determined. The strike prices and expiration dates of the traded options are optimized and tested on 5 different Exchange Traded Funds (ETFs) (DIA, IWM, SPY, XLE, XLF). The performance of the proposed model is compared with Buy and Hold and commonly used technical analysis indicators and the results indicate using optimized options increased the overall profit with less drawdown risk.**

I. Introduction

Implementing successful and profitable trading strategies have been studied both in academia and financial industry for a while. Most of these studies were concentrated on stock market forecasting [1], [2], trend detection [3], and strategy development based on technical indicators. Meanwhile some researchers focused on financial optimization problems such as optimum portfolio allocation [4], technical indicator optimization [5], optimum pairs trading selection, etc. [6]–[10].

Even though there were many studies in financial forecasting and strategy development, not many models combining stocks with options were implemented. Most of the studies that use options were about pricing the options [11]–[13]. Only a handful of studies exist in literature providing options trading strategies [14]–[16]. In this study we propose a two level options spread trading model optimized for the optimum strike price and expiration date for profit maximization.

A. Financial Options

Option is a contract which gives the right to buy or sell a financial asset on a determined date and price. It is not mandatory to use the option. If the option owner comes up with a loss when the option is exercised, he/she would prefer not to use the option, which means the option will expire worthless. Also, American options, which is the preferred option type in our study, can be executed at any time before the expiration date.

There are two types of options, call and put. Options also have different strike prices and different expiration dates. Expiration date indicates the life of an option. The option can be used anytime before the expiration date, but after the expiration date passes, the option ends. Different strike prices indicate the different prices the asset is priced at the expiration date. Option prices increase when the expiration date moves farther away from the current date. Also option prices vary depending on the difference between the strike price and the current price of the asset, the volatility of the asset and the risk-free rate (the environment) where the asset is positioned.

Call options give the right to the owner to purchase a particular asset for a specific price (called strike price) at a given date (called expiration date). The owner would exercise (use) the option if the price of the asset at the expiration date is higher than the strike price, so he/she will have a chance to buy the asset with a lower price than the market. However, if the price of the asset at the expiration date is lower than the strike price, the owner will not exercise the option, as a result the option will expire with a ”0” value, i.e. worthless. However, by using options, the overall risk of the trade is reduced, instead of taking the risk of the price of the asset going much lower, the owner only assumes the risk of the amount he/she paid for the option, which, in general is only a fraction of the asset price. An individual buying a Call option assumes, (or expects) the market will go up, so purchasing a Call option is equivalent to starting a long position in the particular asset with much reduced risk (with some premium, of course).

Put options work in a similar fashion, except, it gives the right to the owner to sell (not purchase) the particular asset for a specific price (strike price) at a given date (expiration date). The owner would exercise (use) the option if the price of the asset at the expiration date is lower than the strike price, so he/she will have a chance to sell the asset with a higher price than the market. However, if the price of the asset at the expiration date is higher than the strike price, the owner will not exercise the option, as a result the option will expire worthless.

Options can be purchased or sold. A buyer of the call option takes a long position, assuming the asset price will increase. However a seller of the call option assumes the asset price will go down, it is similar to purchasing of a put option, instead the only profit the call option seller can benefit is the option price originally obtained for the call. Selling a call option means, at the expiration date, the option seller will have to provide the particular asset at the strike price to the buyer of the call option if the price at the expiration date is

978-1-4799-7492-4/15/$31.00

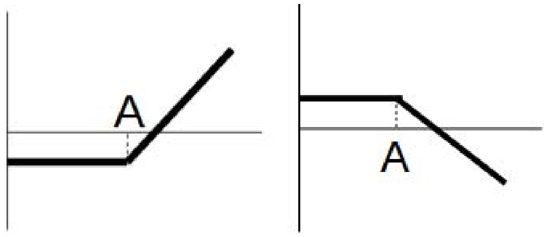

Fig. 1: Buying (left) and Selling (right) a Call Option

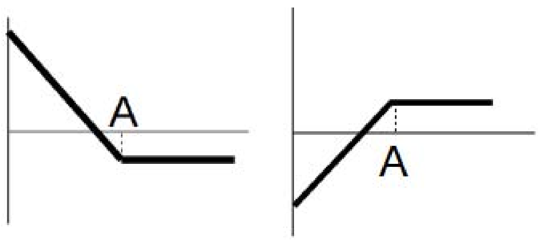

Fig. 2: Buying (left) and Selling (right) a Put Option

higher than the strike price. Unlike the call buyer, which has the option, not obligation, to exercise the option, the call seller has the obligation to provide the corresponding asset if the option buyer prefers to exercise his/her option.

Buying or selling put options works similarly, as in the case of call options. In that case, the buyer of the put option takes a short position, assuming the asset price will decrease. However a seller of the put option assumes the asset price will go up, it is similar to purchasing of a call option, instead the only profit the put option seller can benefit is the option price originally obtained for the put. Selling a put option means, at the expiration date, the option seller will have to purchase the particular asset at the strike price from the buyer of the put option if the price at the expiration date is lower than the strike price. Unlike the put buyer, which has the option, not obligation, to exercise the option, the put seller has the obligation to buy the corresponding asset if the option buyer prefers to exercise his/her option to sell the asset. Figure 1 and Figure 2 demonstrates the profit curve for buying and selling call and put options. In those figures A represents the strike price of the option.

Options are generally used for hedging purposes, they provide an insurance mechanism for a particular investment or trade, however they also have a leveraging effect, since taking long/short positions with options require much less capital than buying/shorting actual assets. As a result, using options as investment/trading tools can be dangerous, so these instruments need to be used carefully in trading systems. In this study, we proposed a trading model which both buys and sells call and put options depending on the underlying asset's (in our study, ETFs) trend. The choice of which particular option type (strike price, expiration date) is chosen by optimization through Particle Swarm Optimization (PSO) and Genetic Algorithms (GA).

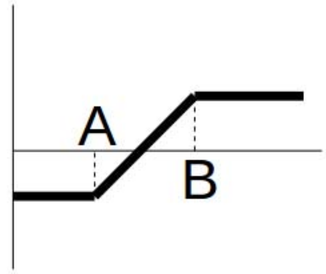

Fig. 3: Bull Call Spread Strategy

B. *Bull Call Spread Option Strategy*

This strategy uses two call options with different strike prices. A call option with lower strike price is bought and another call option of the same ETF with higher strike price is sold at the same time. In figure 3, A is the option's strike price with the lower price and B is the option's strike price with the higher price. Figure 3 can be obtained by combining both subfigures in Figure 1 together, i.e by buying a call option with a strike price A and at the same time selling a call option with a strike price B.

If the ETF's price is higher than both of the options' strike prices, than both of the options will be exercised and the profit will be the difference between the options' strike prices. If the ETF's price is between the strike prices, the purchased call option will be exercised and the sold call option will be worthless. There may be profit or loss according to how close the ETF's price is to A or B. Lastly, if the ETF price is lower than both of the options' strike prices, then both of the options will be worthless and they will not be used, as a result the money assigned for the trade will be lost.

This strategy is useful when the trend is upwards. Since there is a chance to lose all of the invested money, the strategy is risky while the profit is limited, only a portion of the capital should be used in such trades.

C. *Bear Put Spread Option Strategy*

Opposite to Bull Call Spread Option Strategy this method uses two put options with different strike prices. For this strategy, a put option is sold and another put option of the same ETF is bought at same time. Figure 4 shows the possible profit of this strategy. It can be seen from the graph that, when

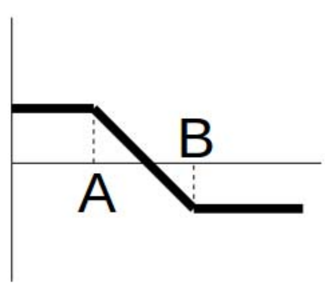

Fig. 4: Bear Put Spread Strategy

the ETF price decreases, the profit increases, but it is limited with the two put options' strike price difference. Figure 4 can be obtained by combining both subfigures in Figure 2 together, i.e by buying a put option with a strike price B and at the same time selling a put option with a strike price A.

This strategy is profitable when the trend is downwards. If the ETF's price increases, there is a chance to lose all the money while the possible profit is limited, just like the case in the Bull Call Spread Strategy, so same precautions need to be taken.

II. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is first introduced by Kennedy and Eberhart in 1995 [17]. This optimization technique is based on bird swarm's movements. In this model, every bird is a solution candidate, named as particle, in the solution space. The particles have a position (x_i) in the space and a velocity vector (v_i) which change their positions with in every iteration. They also keep the information of their best position (p_i) up to that point. The nearest bird to the food or the particle with the best fitness function is called the swarm's best particle and its position is the swarm's best position (g). The particles change their positions with the velocity vector and it is computed with formula 1. In this formula, w is the inertia weight and a values are the speeding multipliers. If speeding multipliers are selected as high values, the particles move fast and they may miss the solution. On the other hand, if multipliers are selected as low values, they move slowly and search time will last longer. In this study w value is selected as 1, and a values are selected as 2. After calculating the velocity, new position is calculated with formula 2.

$$v_i = wv_i + ar(p_i - x_i) + ar(g - x_i) \tag{1}$$

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

PSO implementation starts with placing the particles randomly in the search space. The global best position is the particle's position with the minimum cost function. On every iteration, if a better position is found, global best is updated with the better position. The algorithm ends when the cost function reaches an acceptable value or when a predefined number of iterations is reached.

Particle swarm optimization attracted the attentions of researchers to be used in financial applications, like option pricing [18], predicting financial distress [19] and risk assessment [20]. However it is also possible to use PSO in optimizing trading strategies [24].

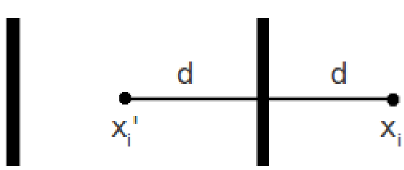

Fig. 5: Boundary handling for Particle Swarm Optimization

In this study the particle vectors have 5 parameters; the expiration dates of the options (the same expiration date is chosen for both options), the difference between the purchased call option's strike price and the ETF's price, the difference between the sold call options's strike price and the purchased call option's strike price and the two parameters for the put option's strike price that are explained above for the call option. The details about how the model works, how an option pair is chosen for initiating a trade is explained in the Model section 4. Every parameter has its maximum and minimum values which are called as search space boundaries. While the particles are moving they should not exceed their boundaries, so for the particles' boundary handling the method in figure 5 is used. In the figure the bold lines represent the boundaries and x_i is the position of the particle that traversed over the boundary. In this method, if a particle moves outside of the boundaries by a distance *d*, it moves back into the boundaries as *d* and its new distance becomes x_i'.

III. Genetic Algorithm

Genetic Algorithm is one of the most used evolutionary algorithm for optimization. This algorithm represents solutions as chromosomes and these chromosomes evolve by cross-over and mutation operations. Every parameter that we are trying to optimize is a gene inside the chromosome.

The cross-over operation is a swap operation between two chromosomes from the population. For this swap, a change point is selected from the chromosomes and the genes after this point are swapped. So, there are two new chromosomes generated from the parent chromosomes. This operation can be made with the selection of one or more points, so there will be more chromosome parts to be swapped. The mutation operation is a change operation on a gene of a chromosome. This operation's probability is very rare and it is essential for not to get stuck on a local optimum. The algorithm finishes when the fitness function goes below a determined value or after limited iterations.

In this study, the cross-over rate is selected as 90% and two points for parting. The mutation rate is selected as 5%, this is chosen higher compared to generally accepted GA standards, because the options trading operations produce highly volatile transactions and we expect to have a large number of local minima among the solution space, so a higher than normal randomness might be beneficial in this particular case. To finalize the algorithm a finalizer limit is set to 100, it means after 100 iterations, the algorithm will finish and the best chromosome will be the result.

Since every set of 100 iterations may finish with different results, the algorithm is run for 5 set of 100 iterations and their best training result obtained from these 5 sets is selected as the best result (also applied in the PSO model the same way)

Gene 1 Expire date	Gene 2 Bought Call Options strike price difference	Gene 3 Sold Call Options strike price difference	Gene 4 Bought Put Options strike price difference	Gene 5 Bought Put Options strike price difference

Fig. 6: Chromosome structure

Genetic algorithms are also used in financial applications the same way as PSO or the other evolutionary computation techniques were applied. Some of these implementations include Portfolio selection [4] and market prediction [21]. In this study the chromosome structure for the GA implementation had the same vector parameters as in PSO model (5 genes: 2 for call option strike prices, 2 for put option strike prices, 1 for the common expiration date)

IV. Two-Level Option Pair Trading Model

This developed model consists of two levels. The first level determines the trend using SMA, while the second level uses two different option strategies according to the trend. The option strategies and levels of the model are explained in the next sections.

For this model, in every trade 10% of the capital is used for the transaction which includes buying the lower priced call/put option and selling the higher priced call/put option. As a result, even if both options expire worthless, the total loss will not exceed 10% of the whole investment. When buying the option, the bid price is assumed meanwhile the ask price is used when selling. So, the spread difference is used during the study, no extra commissions are considered.

A. First Level

The purpose of the first level is to determine the trend, if it is upwards or downwards. The easiest way to determine the trend change points is to find the local extreme points. The local extremes are found with the window panning method. This method selects a 30 day period from the beginning and pans the 30 day window through the end of the period. The minimum and maximum values are selected as the local extreme points and they show the trend change points. On the other hand, the window panning method can not be used for real time calculations, because it needs the future values to determine the minimum or maximum value.

To find the trend change points, Simple Moving Average (SMA) is another way. SMA is the average of closing prices of an ETF for a predefined number of days. The formulation of SMA is shown in formula 3. For trend determination two SMAs with different number of days are used. If the short term SMA crosses over the long term SMA, it is considered as an uptrend and otherwise it is considered as a downtrend.

$$SMA = \frac{\sum_{i=d-N}^{d} p_i}{N} \tag{3}$$

For fitness function, the similarity of the window panning method and the SMA method is used. To calculate the similarity between the two methods, their consistency is calculated by comparing the points found by the two methods.

The possible SMA values are between 5-100 for the short term, and between 10-200 for the long term. Since the search values are limited and can be computed in a short time, this level is calculated with a brute force algorithm. There is a restriction in the algorithm such that the short term SMA value can not be larger than the long term SMA value.

The results of first level of 5 ETFs are shown in Table I.

TABLE I: Short term and Long term SMA values of 5 ETFs used for trend determination

ETF	SMA short	SMA long
DIA	8	22
IWM	8	21
SPY	7	24
XLE	14	25
XLF	9	17

B. Second Level

In this level the bull/bear spread option strategies are used. The trend is decided in the first level and this level uses this information to determine which option strategy will be considered. If the trend of the ETF is upwards, Bull Call Spread Option strategy will be used and if the trend is downwards, Bear Put Spread Option strategy will be used.

Meanwhile, the fitness function that will be used in this level is the Sharpe ratio which is developed by William F. Sharpe in 1966 [22]. Sharpe ratio is a performance analysis method, considering risk. Its current version and the version used in this study are developed in 1998 [23]. The formulation is shown below. The algorithms run to maximize the Sharpe ratio value.

$$SharpeRatio = \frac{\textit{Expected return} - \textit{Risk free rate}}{\textit{Standart deviation}} \tag{4}$$

The option strategies are risky operations, but they can be very profitable at the same time. If the fitness function is selected as profit, the model will be trained as highly profitable but at the same time it will be risky. As a result, while the training period produces a high profit, mostly because of a few lucky, but highly profitable trades, the test period ends up with losing a considerable portion of the money. So, in this study, the Sharpe ratio which provides a balance between profit and risk is used as the fitness function. In equation 4, the expected return is the total profit of the transactions, the denominator is the standard deviation of the transactions' profits. Risk free rate is set to 0, because it has no effect on the comparison of different Sharpe values.

The results of 5 ETFs used in this study are listed in Table II and Table III, respectively for Genetic Algorithm and Particle Swarm Optimization. In tables II, III, V and VI SR represents the Sharpe Ratio value, Ann.P. represents the annualized profit.

TABLE II: Option pair strategy results of second level with GA

ETF	Train SR	Train Ann.P.	Test SR	Test Ann.P.
DIA	0.39	31.86	0.18	36.74
IWM	0.13	55.04	0.16	44.22
SPY	0.26	49.75	0.06	10.51
XLE	0.23	8.44	-0.07	-6.64
XLF	0.18	11.76	0.04	6.68

The statistical results for IWM is shown in Table IV. For Genetic Algorithm and Particle Swarm Optimization results there are two columns and each of them show the training and testing period results separately. Total profit shows the

TABLE III: Option pair strategy results of second level with PSO

ETF	Train SR	Train Ann.P.	Test SR	Test Ann.P.
DIA	0.43	31.48	0.20	16.48
IWM	0.13	56.09	0.09	26.44
SPY	0.35	50.19	0.11	18.57
XLE	0.26	7.91	-0.04	-3.03
XLF	0.18	11.76	0.08	15.23

TABLE IV: Statistical results for IWM options transactions with GA and PSO

	Genetic Algorithm		Particle Swarm Opt.	
	Train	Test	Train	Test
Total Profit	753.78	199.37	782.52	101.87
Annual Profit	55.04	44.22	56.09	26.44
Transaction Count	14	10	13	10
Avg. Tran. per Year	2.86	3.34	2.66	3.34
Positive Tran. Rate(%)	100	90	100	70
Avg. Profit per Tran.(%)	167.71	122.67	184.87	82.69
Avg. Trade Period (days)	93	86	103	92
Max. Tran. Profit (%)	314.63	347.76	308.16	347.76
Max. Tran. Loss (%)	-	100	-	100
Min. Portfolio Value ($)	100000	100000	100000	100000
Max. Portfolio Value ($)	853776.86	313864.65	882518.66	235160.66

difference of the capital between the end and the beginning of training or testing period. The annual profit is calculated by dividing the total profit to the number of years of the corresponding (training or test) period. Transaction count is the number of total transactions in the corresponding period and Average Transaction per Year is the average number of transactions per year of the corresponding period. Positive transaction rate is the rate of transactions with positive income. Average profit per Transaction is the average rate of the income of every transaction made in the corresponding time period. Average trade period is the average number of days between the beginning and the end of transactions. Maximum transaction profit and loss, shows the rate of maximum income and loss of a transaction respectively. Maximum and minimum portfolio values show the maximum and minimum of the total cash and asset values in portfolio in dollars.

Figure 7 and Figure 8 show an example graph of portfolio value change for IWM option transaction in train and test time periods.

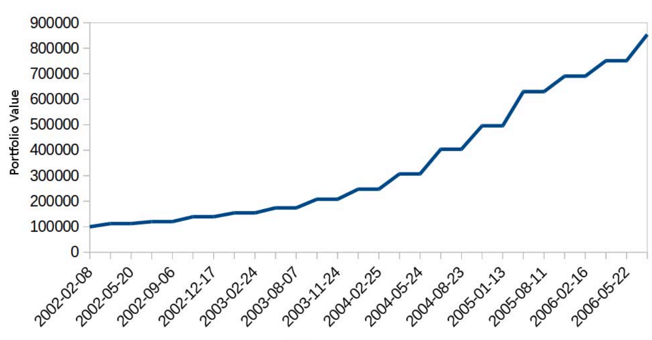

Fig. 7: Portfolio value of IWM option transactions in train time with GA

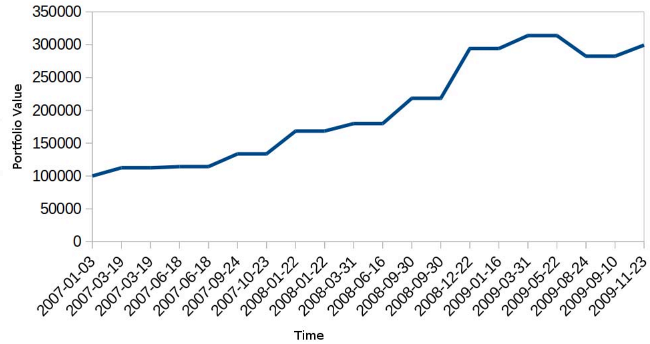

Fig. 8: Portfolio value of IWM option transactions in test time with GA

V. Results and Discussions

The model is tested on 5 ETFs; DIA, IWM, SPY, XLE and XLF. Table V and Table VI show the results for 5 ETFs' average Sharpe ratio and average annual profits with two evolutionary algorithms, Genetic Algorithm and Particle Swarm Optimization. The model is optimized by using training data between 2002 and 2007. The optimized model is tested using data between 2008-2009. The average results on the tables are slightly different, because the algorithms are heuristic algorithms and their approach to the best solution is different as stated in section 2 and section 3.

TABLE V: Comparison of 4 different strategies optimized with GA

Model	Train SR	Train Ann.P.	Test SR	Test Ann.P.
Buy & Hold	0	9.09	0	-1.98
2-level Covered Call	0.50	30.20	-0.01	-3.94
3-level Covered Call	0.45	23.94	0.14	4.29
Option Pair Spread Str.	0.24	31.37	0.07	18.30

TABLE VI: Comparison of 4 different strategies optimized with PSO

Model	Train SR	Train Ann.P.	Test SR	Test Ann.P.
Buy & Hold	0	9.09	0	-1.98
2-level Covered Call	0.51	20.72	0.02	2.85
3-level Covered Call	0.66	43.89	0.17	11.75
Option Pair Spread Str.	0.27	31.49	0.09	14.74

This developed model is compared with 3 different strategies. Buy & Hold is the base strategy used in most financial methods. This method buys an ETF on beginning day and sells on the last day. There is no other transaction between the first and last days. In tables V and VI, Buy & Hold model values are the same because there is no strategy and the same ETFs are used for both evolutionary algorithms, also the ETFs' prices are the same, so the results for Buy & Hold are identical. Sharpe Ratio values for Buy & Hold are 0, because Sharpe ratio is used to evaluate consistency between transactions and there is only one transaction in Buy & Hold, hence the Sharpe ratio for Buy & Hold can not be calculated.

2-Level Covered Call model uses ETFs and options together [24] and it also optimizes the strike price and expiration dates of options, but there is no trend determination. Another work, 3-Level Covered Call model [25] adds trend determination level to the 2-Level model and it is observed that the 3-level model makes more profit than the 2-level model.

The proposed model in this paper, uses only options for trading and the tables V and VI show that, this model performed better than the base, Buy & Hold, and other models while keeping the risk at an acceptable level. However, only 10% of the whole capital is used in each trade. Further analysis is required to determine what the optimum percentage of capital spared for each trade should be.

VI. Conclusion

In this study, a two level options trading strategy for uptrend or downtrend conditions is developed. In the first level, the overall trend is determined and this information is passed to the second level where the appropriate option strategy is decided. During the uptrend case, a Bull call spread strategy, during the downtrend case, the bear put spread strategy is used. The corresponding strike prices and expiration dates of the option pairs are optimized using PSO and GA methods. The results indicate that this model has produced better profitable trades with less risk compared to Buy and Hold and some previously studied models. Meanwhile, there might be other profitable options and/or hybrid trading strategies with less exposed risk, these need to be investigated too. However, the preliminary results that are obtained through using this particular option strategy is promising, and the model can be used as part of a trading model with appropriate configuration.

References

[1] E. Hadavandi, H. Shavandi, and A. Ghanbari, "Integration of genetic fuzzy systems and artificial neural networks for stock price forecasting," *Knowledge-Based Systems*, vol. 23, no. 8, pp. 800–808, 2010.

[2] G. S. Atsalakis and K. P. Valavanis, "Surveying stock market forecasting techniques–part ii: Soft computing methods," *Expert Systems with Applications*, vol. 36, no. 3, pp. 5932–5941, 2009.

[3] C. Kearney and S. Liu, "Textual sentiment in finance: A survey of methods and models," *International Review of Financial Analysis*, 2014.

[4] R. Ruiz-Torrubiano and A. Suárez, "Hybrid approaches and dimensionality reduction for portfolio selection with cardinality constraints," *Computational Intelligence Magazine, IEEE*, vol. 5, no. 2, pp. 92–107, 2010.

[5] A. M. Ozbayoglu and U. Erkut, "Stock market technical indicator optimization by genetic algorithms," in *Intelligent Engineering Systems through Artificial Neural Networks, Volume 20*. ASME Press, 2010.

[6] R. Majhi, G. Panda, and G. Sahoo, "Development and performance evaluation of flann based model for forecasting of stock markets," *Expert Systems with Applications*, vol. 36, no. 3, pp. 6800–6808, 2009.

[7] T. Kamo and C. Dagli, "Hybrid approach to the japanese candlestick method for financial forecasting," *Expert Systems with applications*, vol. 36, no. 3, pp. 5023–5030, 2009.

[8] P.-C. Chang and C.-H. Liu, "A tsk type fuzzy rule based system for stock price prediction," *Expert Systems with Applications*, vol. 34, no. 1, pp. 135–144, 2008.

[9] A. Canelas, R. Neves, and N. Horta, "A sax-ga approach to evolve investment strategies on financial markets based on pattern discovery techniques," *Expert Systems with Applications*, vol. 40, no. 5, pp. 1579–1590, 2013.

[10] W. Leigh, R. Purvis, and J. M. Ragusa, "Forecasting the nyse composite index with technical analysis, pattern recognizer, neural network, and genetic algorithm: a case study in¡ i¿ romantic¡/i¿ decision support," *Decision Support Systems*, vol. 32, no. 4, pp. 361–377, 2002.

[11] S.-E. Yu, M. Li, H. K. Leon, T.-H. Chen, and C.-Y. Chen, "Model construction of option pricing based on fuzzy theory," *Journal of Marine Science and Technology*, vol. 19, no. 5, pp. 460–469, 2011.

[12] H.-C. Wu, "European option pricing under fuzzy environments," *International Journal of Intelligent Systems*, vol. 20, no. 1, pp. 89–102, 2005.

[13] M. Tsukui and K. Furuta, "An option pricing by eliminating observation noise when the model parameters are unknown," *International journal of systems science*, vol. 28, no. 12, pp. 1259–1283, 1997.

[14] S.-C. Huang, C.-C. Li, C.-W. Lee, and M. J. Chang, "Combining ica with kernel based regressions for trading support systems on financial options," in *Advances in Intelligent Decision Technologies*. Springer, 2010, pp. 163–169.

[15] W. L. Tung and C. Quek, "Financial volatility trading using a self-organising neural-fuzzy semantic network and option straddle-based approach," *Expert Systems with Applications*, vol. 38, no. 5, pp. 4668–4688, 2011.

[16] H.-J. Sheu and Y.-C. Wei, "Effective options trading strategies based on volatility forecasting recruiting investor sentiment," *Expert Systems with Applications*, vol. 38, no. 1, pp. 585–596, 2011.

[17] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Neural Networks, 1995. Proceedings., IEEE International Conference on*, vol. 4, Nov 1995, pp. 1942–1948 vol.4.

[18] H. Prasain, G. Jha, P. Thulasiraman, and R. Thulasiram, "A parallel particle swarm optimization algorithm for option pricing," in *Parallel Distributed Processing, Workshops and Phd Forum (IPDPSW), 2010 IEEE International Symposium on*, April 2010, pp. 1–7.

[19] J. Zhou, T. Bai, J. Tian, and A. Zhang, "The study of svm optimized by culture particle swarm optimization on predicting financial distress," in *Automation and Logistics, 2008. ICAL 2008. IEEE International Conference on*. IEEE, 2008, pp. 1054–1059.

[20] Q. Huang, "Fuzzy support vector machine using particle swarm optimization for high-tech enterprises financing risk assessment," in *Computational and Information Sciences (ICCIS), 2013 Fifth International Conference on*. IEEE, 2013, pp. 670–673.

[21] H. Huang, M. Pasquier, and C. Quek, "Financial market trading system with a hierarchical coevolutionary fuzzy predictive model," *Evolutionary Computation, IEEE Transactions on*, vol. 13, no. 1, pp. 56–70, 2009.

[22] W. F. Sharpe, "Mutual fund performance," *Journal of business*, pp. 119–138, 1966.

[23] W. F. Sharpe, "The sharpe ratio," *Streetwise–the Best of the Journal of Portfolio Management*, pp. 169–185, 1998.

[24] M. Ucar, I. Bayram, and A. M. Ozbayoglu, "A two-level cascade evolutionary computation based covered call trading model," *Procedia Computer Science*, vol. 20, no. 0, pp. 472 – 477, 2013, complex Adaptive Systems. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1877050913011058

[25] I. Bayram, "Three level covered call options trading model optimized with evolutionary algorithms," Master's thesis, TOBB University of Economics and Technology, 8 2014.