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Optimizing MACD Parameters via Genetic Algorithms for Soybean Futures

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Abstract

To create profits, traders must time the market correctly and enter and exit positions at ideal times. Finding the optimal time to enter the market can be quite daunting. The soybean market can be volatile and complex. Weather, sentiment, supply, and demand can all affect the price of soybeans. Traders typically use either fundamental analysis or technical analysis to predict the market for soybean futures' contracts. Every agricultural future's contract or security contract is different in its nature, volatility, and structure. Therefore, the purpose of this research is to optimize the moving average convergence divergence parameter values from traditionally used integers, to values that optimize the profit of the soybean market.

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1. Introduction

By studying a market, an individual can create a “trading strategy” or heuristic set of rules to buy or sell a contract [1]. Traders typically use either fundamental analysis or technical analysis to predict the market of soybean futures' contracts. Technical analysis investigates historical prices to create strategies [2]. Fundamental analysis, however, investigates the intrinsic value of an investment using company news releases and financial statements [3]. This research will use technical analysis and computational intelligence to create a trading strategy.

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Many methods have been used to trade soybean future contracts, for example, the relative strength index (RSI), moving averages, stochastic, or moving average convergence divergence (MACD) [4]. Traders have their own preferences and there is no one given trading strategy that is the best [5].

Every agricultural future’s contract or security contract is different in its nature, volatility, and structure. Moreover, making predictions in a market is not an easy task for a trader, as financial data tends to be non-linear, uncertain, and non-stationary [5]. Therefore, the purpose of this research is to optimize the moving average convergence divergence parameters from traditional numbers to ones more acceptable to the soybean market.

2. Literature review and methodology

2.1 Moving average convergence divergence (MACD)

The moving average convergence divergence, or more commonly known as the MACD, is a widely used technical trading tool. MACD is used to find turning points in the market that indicate buy and sell signals [6]. The MACD is calculated as follows: first, find the 12-day exponential moving average of the commodity, referred to as the fast moving average; second, find the 26-day exponential moving average of the commodity, referred to as the slow moving average. The fast moving average minus the slow moving average creates the MACD line. Next, a signal line is created; this is the 9-day moving average of the MACD [6]. Subtracting the signal line from the MACD creates a MACD histogram. The MACD formulas are provided in equations (1)-(5).

$$EMA_{fast} = (2/(N_1+1)) * (Close - EMA_{fast}(previous\ day)) + EMA_{fast}(previous\ day) \tag{1}$$

$$EMA_{slow} = (2/(N_2+1)) * (Close - EMA_{slow}(previous\ day)) + EMA_{slow}(previous\ day) \tag{2}$$

$$MACD = EMA_{fast} - EMA_{slow} \tag{3}$$

$$Signal\ Line = (2/(N_3+1)) * (MACD - EMA_{MACD}(previous\ day)) + EMA_{MACD}(previous\ day) \tag{4}$$

$$MACD_{histogram} = MACD - Signal\ line \tag{5}$$

The figure below is a graphical representation of equations (1)-(5).

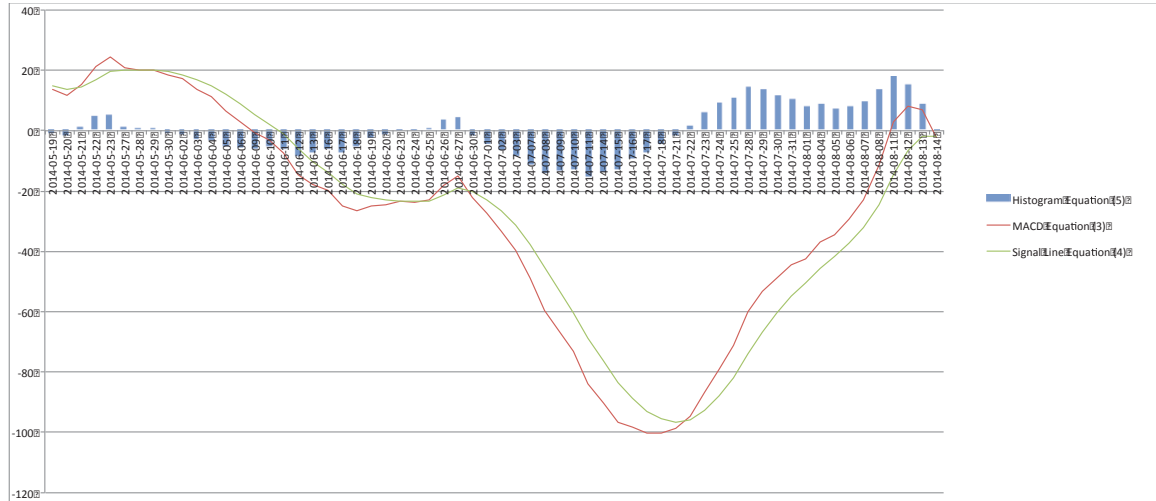


Fig. 1 Relationship of MACD equations (1)-(5).

The buy and sell signals for the MACD are adapted in Table 1 below [1].

Table 1. MACD heuristics.

| | |
|------|---|
| Buy | $(MACD < 0)$ and $(MACD_{histogram} < 0)$ |
| Sell | $(MACD > 0)$ and $(MACD_{histogram} > 0)$ |
| Hold | Else |

Table 2 shows a second set of buy and sell signals for the MACD that look specifically for crossovers, where i is the day.

Table 2. MACD crossover heuristics.

| | |
|------|---|
| Buy | $(MACD < 0)$ and $(MACD_{histogram}(i-1) < 0)$ and $(MACD_{histogram}(i) > 0)$ |
| Sell | $(MACD > 0)$ and $(MACD_{histogram}(i-1) > 0)$ and $(MACD_{histogram}(i) < 0)$ |
| Hold | Else |

Previous work has used MACD as an indicator in a weighted model with other indicators [7]. Other models have tried to optimize the MACD parameter values to a particular market [8].

2.2 Genetic algorithms (GA)

Genetic algorithms have the ability to take an infinitely large solution space and test various possible solutions in a natural selection manner. Genetic algorithms also have the ability to obtain results when there are multiple local maxima and minima in a function, and unlike gradient methods, do not get caught in suboptimal maxima and minima. Thus, in examining the problem as a whole, if the population can find a better value in the function then it is still acceptable [9]. This makes genetic optimization ideal in dealing with financial market data, as one may enter and exit the market multiple times.

Genetic algorithms evaluate a fitness function in a natural selection optimization manner, such that the fitness is maximized and error is minimized [9][10]. The methodology of genetic algorithms can be observed in the flow chart in Figure 2 [10].

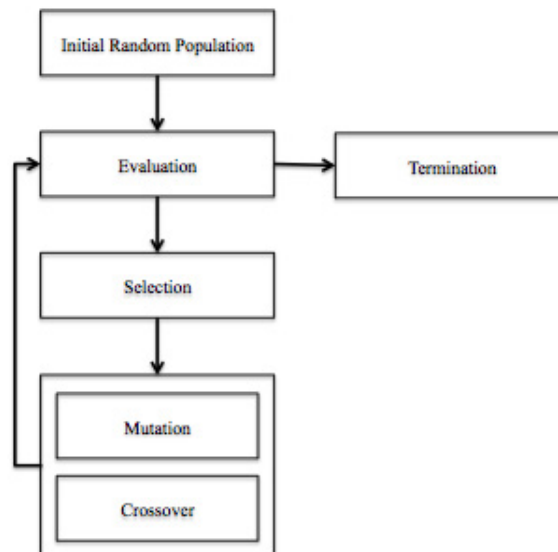


Fig. 2. Genetic algorithm methodology flow chart [10].

An initial random population is created and then assessed utilizing a defined fitness function. The population size was set to 100 as previous research has found that 100 is the optimal population size for speed and accuracy [11]. If the minimum error is reached in evaluation, or other stopping criteria are met, the genetic algorithm terminates, otherwise it moves down the flow chart in Figure 2.

From this, subsequent populations are created. There are many different methods for creating the next generation [12]. In this research the following explanations are applied. A score is given to each chromosome in the population via the fitness value. An elite set of high-ranking children is then selected for the next generation. Next, two very important things happen: crossovers and mutation. To create a crossover or mutated child, parents are needed. Tournament style is one of the methods in selecting parents. Tournament style has received increasing usage and popularity, as it is acceptable in both parallel and non-parallel architectures [12]. Tournament style randomly selects n chromosomes and the highest-ranking chromosome in this pool becomes the parent [13]. Tournament style is robust selection method and has been shown to work well with noisy fitness functions [12]. In this research n is set to four.

Crossover children are produced with a two-point crossover function, such that the parents are spliced into two points and recombine to create a child offspring. Next, mutated children are created. Mutations are created by slightly changing the parent chromosome in a random manner. For integer constraints, an adaptive feasible method is used where the program creates a mutated child that is based of the previous generation, but still meets the constraints [13].

New chromosomes are crossed-over with a probability, c (0.8). From the scores given to the chromosomes, the best scores are considered elite. A total of 5% of the population is elite and therefore not altered for the next generation. The remaining population is mutated. With the population size of 100, this gives 5 elite children, 76 crossover children, and 19 mutated children. New generations occur until the minimum fitness is reached. For this work, genetic algorithms are used to optimize N_1 , N_2 , and N_3 from equations (1), (2), and (4), respectively. The fitness function is defined to maximize profits, or Sales Price-Purchase Price, from the soybean futures contract.

3. Results

Data was collected from the CME August 2014 soybean contract (SQ2014) from 01-03-2012 to 08-14-2014. This gave 500 data points for optimizing the MACD parameters, from 01-03-2012 to 12-24-2013, along with 160 data points for testing the optimized MACD parameters, from 12-26-2013 to 08-14-2014. All prices are quoted in cents per bushel. Assumptions were made with regard to profit maximization. It was assumed there were no transaction costs, there was liquidity to place all trades, and all trades had to be settled the last trading day of the contract.

3.1 Buy-and-hold strategy

Figure 3 provides the price of soybeans from 12-26-2013 to 08-14-2014. In a simple buy-and-hold strategy, one buys on the first day of testing and sells on the last day of testing.

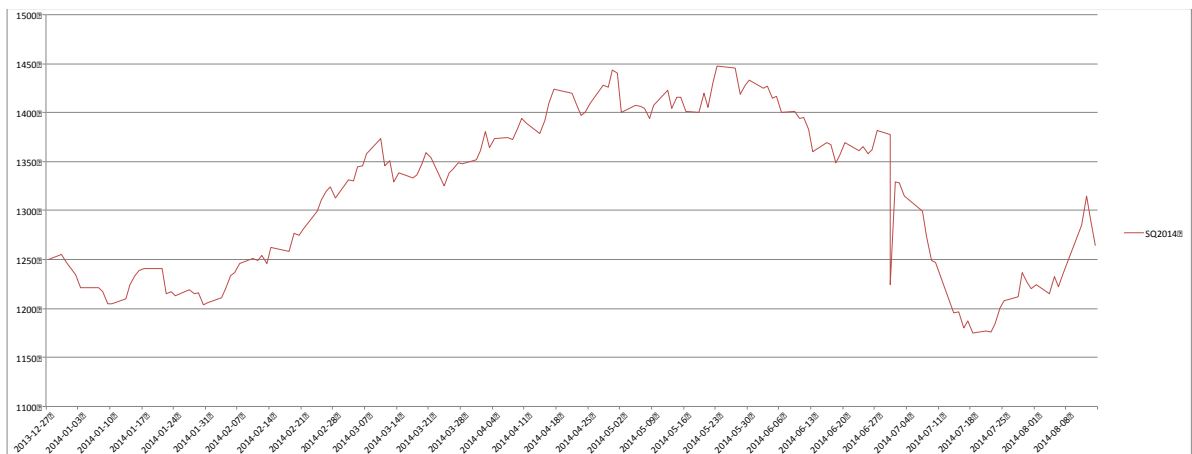


Fig. 3 SQ2014 soybean prices.

Table 3. Buy-and-hold strategy.

| | |
|---|-------|
| Buy Signals | 1 |
| Sell Signals | 1 |
| Profit (in cents per bushel for all trades) | -25.3 |

3.2 Traditional MACD (12,26,9)

Figure 4 is the MACD (12,26,9) for a fast moving average of 12 days, a slow moving average of 26 days, and a signal line of 9 days.

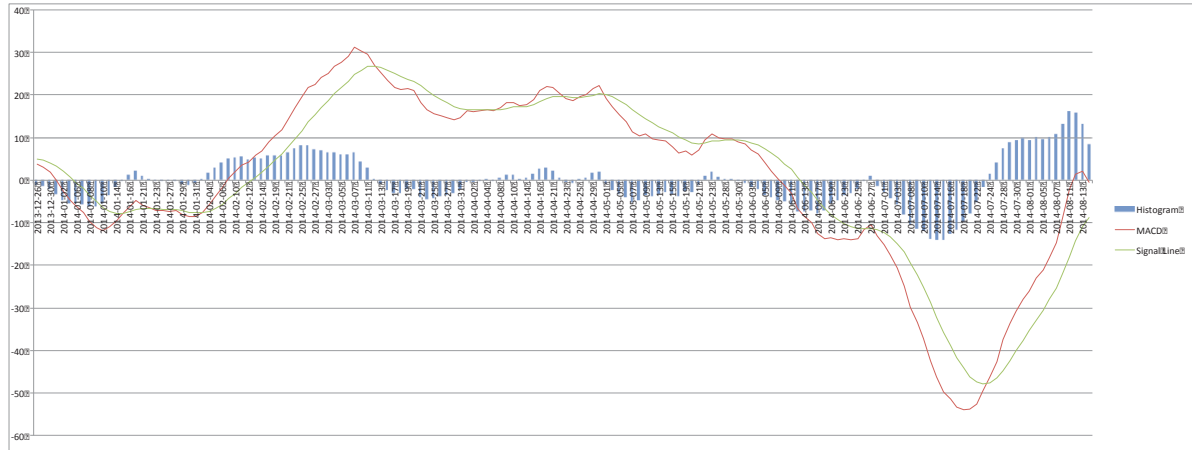


Fig. 4. Traditional MACD (12,26,9).

3.2.1 MACD heuristics (12,26,9)

Using the heuristics developed in Table 1, the following results in Table 4 are obtained.

Table 4. MACD heuristics (12,26,9).

| | |
|---|--|
| Buy Signals | 48 |
| Sell Signals | 45 (3 extra sell contracts had to be placed at the end of the contract period to settle) |
| Profit (in cents per bushel for all trades) | 3906.0 |
| Profit in cents per round trip | 81.4 |

This created two buy and two sell trends based on the defined crossovers.

3.2.2 MACD crossover heuristics (12,26,9)

Using the heuristics developed in Table 2, the following results in Table 5 are obtained.

Table 5. MACD crossover heuristics (12,26,9).

| | |
|---|---|
| Buy Signals | 4 (1 extra buy contract had to be placed at the end of the contract period to settle) |
| Sell Signals | 5 |
| Profit (in cents per bushel for all trades) | 664.5 |
| Profit in cents per round trip | 132.9 |

3.3 Genetic algorithm MACD

3.3.1 Genetic algorithm MACD heuristics (11.017,32.925,16.467)

Figure 5 provides the results of the Genetic Algorithm MACD (11.017,32.925,16.467), which uses a fast moving average of 11.017 days, a slow moving average of 32.925 days, and a signal line of 16.467 days. The parameter values optimized in 55 generations. Using the heuristics in Table 1, the results in Table 6 were obtained.

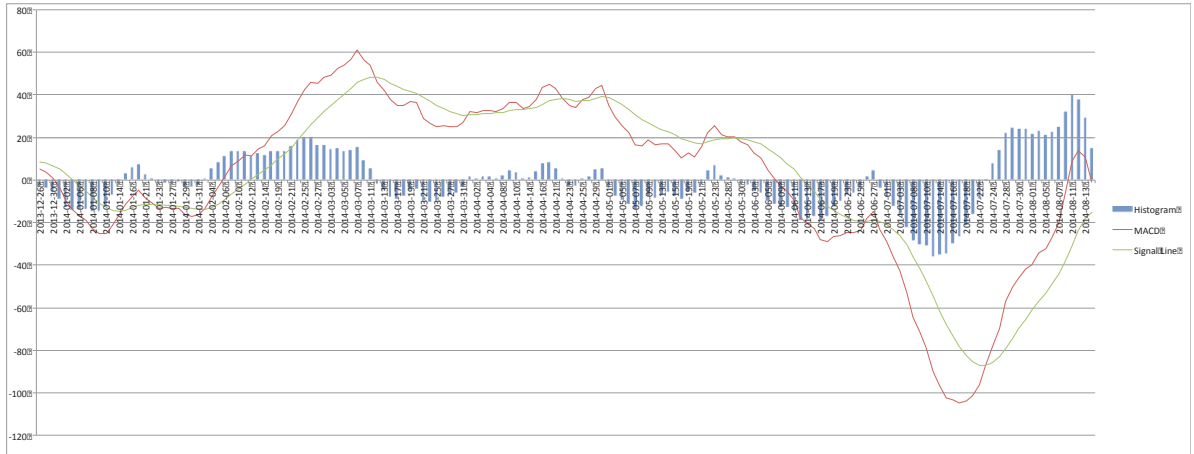


Fig. 5. Genetic algorithm MACD (11.017,32.925,16.467).

Table 6. Genetic algorithm MACD heuristics (11.017,32.925,16.467).

| | |
|---|---|
| Buy Signals | 47 (3 extra buy contracts had to be placed at the end of the contract period to settle) |
| Sell Signals | 50 |
| Profit (in cents per bushel for all trades) | 4507.0 |
| Profit in cents per round trip | 90.1 |

3.3.2 Genetic algorithm MACD crossover heuristics (6.866,33.812,4.575)

Figure 6 provides the Genetic Algorithm MACD (6.866,33.812,4.575) for a fast moving average of 6.866 days, a slow moving average of 33.812 days, and a signal line of 4.575 days. The parameter values optimized in 54 generations.

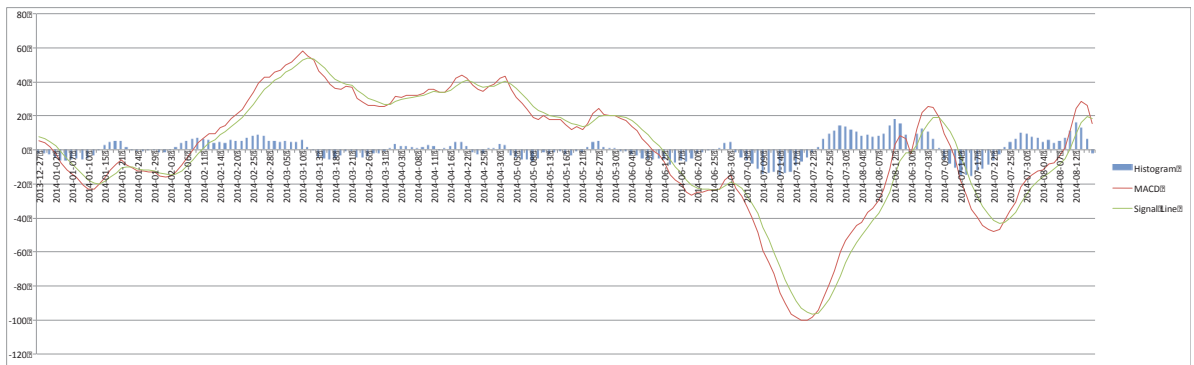


Fig. 6. Genetic algorithm MACD crossover (6.866,33.812,4.575).

Using the heuristics developed in Table 2, the following results in Table 7 are obtained.

Table 7. Genetic algorithm MACD crossover heuristics (6.866,33.812,4.575).

| | |
|---|---|
| Buy Signals | 4 (1 extra buy contract had to be placed at the end of the contract period to settle) |
| Sell Signals | 5 |
| Profit (in cents per bushel for all trades) | 728.0 |
| Profit in cents per round trip | 145.6 |

4. Conclusions

In conclusion, this research has shown that the soybean futures contract is different in its nature, volatility, and structure. Using traditional MACD numbers (12,26,9) does not provide as much profit as using optimized numbers. Previous methods have found similar numbers for the MACD: a fast moving average of 5 days, a slow moving average of 34 days, and a signal line of 7 days [14]. These results and numbers are also close to numbers found in the Fibonacci sequence.

Moreover, optimizing for regime shifts and placing funds on additional contracts can generate more profits. The Genetic Algorithm MACD Crossover Heuristics model (section 3.3.2), with increased volume of trading, has the highest profit possibility of all the models. Using the new crossover heuristic (Table 2) generates better profits in cents per round trip for both the traditional MACD and the Genetic Algorithm MACD models.

This research shows that while traditional technical trading does have a place in the futures market, computational intelligence can be used to create better models more suited to individual contracts. Using computational methods such as genetic algorithms can take an existing technical model and increase its profitability for traders.

5. References

1. Nitisopa, W., & Srijuntongsiri, G. (2012, December). Improving trading strategies by optimizing the weighted combination of different trading strategies. *Mathematical Methods for Information Science & Economics: Proceedings of the 17th WSEAS International Conference on Applied Mathematics (AMATH 12)*, pp. 29-31.
2. Edwards, R. D., Magee, J., & Bassetti, W. H. C. (2007). *Technical analysis of stock trends*. CRC Press.
3. Qin, Q., Wang, Q., Li, J., & Ge, S. (n.d.). Linear and Nonlinear Trading Models with Gradient Boosted Random Forests and Application to Singapore Stock Market. *JILSA Journal of Intelligent Learning Systems and Applications*, pp. 1-10.
4. Kwon, Y., & Moon, B. (2003). Daily Stock Prediction Using Neuro-genetic Hybrids. *Genetic and Evolutionary Computation — GECCO 2003 Lecture Notes in Computer Science*, pp. 2203-2214.
5. Kwon, Y. K., & Moon, B. R. (2007). A hybrid neurogenetic approach for stock forecasting. *IEEE Transactions on Neural Networks*, 18(3), pp. 851-864.
6. Aspray, T. (1989). Individual stocks and MACD. *Technical Analysis of Stocks & Commodities*, 7(2), pp. 56-61.
7. Badawy, F., Abdelazim, H. Y., & Darwish, M. G. (2005, December). Genetic algorithms for predicting the Egyptian stock market. *ITI 3rd International Conference on Information and Communications Technology, 2005. Enabling Technologies for the New Knowledge Society*, pp. 109-122.
8. Marques, F. C., Gomes, R. M., de Almeida, P. E., Borges, H. E., & Souza, S. R. (2010, July). Maximization of investment profits: An approach to MACD based on genetic algorithms and fuzzy logic. *2010 IEEE Congress on Evolutionary Computation (CEC)*, pp. 1-7.
9. Rojas, R. *Neural networks: a systematic introduction*, 1996.
10. Dagli, C. H., Singh A., Dauby, J. P., & Wang, R. (2009, December). Smart systems architecting: computational intelligence applied to trade space exploration and system design. *Systems Research Forum*, Vol. 3, No. 02, pp. 101-119. World Scientific Publishing Company.
11. Roeva, O., Fidanova, S., & Paprzycki, M. (2013, September). Influence of the population size on the genetic algorithm performance in case of cultivation process modeling. *2013 Federated Conference on Computer Science and Information Systems (FedCSIS)*, pp. 371-376.
12. Miller, B. L., & Goldberg, D. E. (1995). Genetic algorithms, tournament selection, and the effects of noise. *Complex Systems*, 9(3), pp. 193-212.
13. Documentation-How the Genetic Algorithm Works. (n.d.). Retrieved March 18, 2015, from <http://www.mathworks.com/help/gads/how-the-genetic-algorithm-works.html>.
14. Elder, A. (1993). *Trading for a living: Psychology, trading tactics, money management*. New York: J. Wiley.