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Applying Machine Learning Approach to Build an Automated Trading System for Gold Chart

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ABSTRACT
Nowadays, with the pervasiveness of online and algorithmic trading, there is a need to analyze financial markets' trading data and turn them into profitable decisions in the shortest time possible. The purpose of this study is to develop an automated algorithmic trading system using AI (Artificial Intelligence) in the global gold market. In recent years, employing AI to build profitable strategies has considerably increased. In this paper, to create a trading system, the genetic algorithm is employed to optimize the two functions of net profit and return on conditional risk and technical analysis. Also, to complete the risk management system, the optimum profit and loss limit for the market is set. The results show that the generated trading system has a more favorable return-to-risk ratio than other competing strategies. A 30-minute timeframe is also suitable for building trading systems on gold.

General Terms
Prediction, Genetic Algorithm, Artificial Intelligence

Keywords
Algorithmic trading, gold, technical analysis, strategy, genetic algorithm

1. INTRODUCTION
Algorithmic trading is a type of automated trading for sending orders along with decision algorithms, which are based on unique ordering parameters such as time, price, or order quantity.

There are three types of analysis used in financial markets.Technical analysis is the first method that is done by examining price charts and technical indicators based on the trading history of a financial index.

Fundamental analysis is the second method, which is based on the performance of companies and their profitability growth.Finally, behavioral-financial analysis is the third method which is a field of financial knowledge thatbenefits from psychological theories to explain the behavior of financial markets.

Artificial Intelligence has also been used to predict the market recently, which might lead to the creation of automated algorithmic trading systems, combined with technical analysis.

To create strategies, cryptographers and market experts currently consider various methods, but for everyone, finding the best prices to trigger and close the trades is the primary goal. However, these methods are usually time-consuming and costly. Therefore, researchers have long sought to develop other methods. It is less than a decadeandartificial intelligence is becoming the focus of so much attention and scientists' willingness to find strategies to buy and sell shares in different markets.

One of the first errands performed in association with creating an automated trading system by combining technical analysis, optimization algorithms, and artificial intelligence is Skabar and Klote [1], who utilized genetic algorithms and neural networks to determine points of entry and exit for commodity exchanges. Some researchers have also worked on optimizing the parameters of technical indicators, among which [2] can be mentioned.

In [3],the researcher, using a genetic algorithm, has tried to optimize the parameters of various technical indicators. Algorithmic trading systems are beneficial in various areas of financial issues such as modeling and forecasting stock prices, [4] portfolio management, and optimization [5].

In [6], to predict the trend to determine the buying and selling points of assets,multi-objective genetic algorithms have developed their approach training a trading system. In this study, two objective functions of rate of return and variance of returns have been used. Also, in [7], aiming to optimize the combination of technical indicators, a multi-objective particle swarm optimization algorithm has been applied and desirable resultswere obtained. In this study [8], the parameters of technical indicators have been optimized using the PSO (Particle Swarm Optimization) algorithm, the results of which have been acceptable.

In [9], anentry/reverse trading system using Bollinger Bands on energy futures contracts is presented. It also examines the effects of using different indicators in building an automated trading system for the stock futures market. The recent system has achieved significant efficiency compared to other methods. They suggested using the system on commodity-based futures such as gold. [10] deals with portfolio optimization using fuzzy logic and particle optimization algorithm. In [11], a decomposition-selection-group prediction system is provided to predict the future price of energy based on the multi-objective version of the chaos game optimization algorithm. [12] presents a new forecasting model with an envelope-based feature selection approach using a multi-objective optimization technique for crude oil time series.

[13] predicts time series in financial markets using a combination of turbulence theory, multilayer perceptron, and multi-objective evolution algorithms.

One of the important features of technical indicators is the bilateral analysis of financial assets. This conveys that the indicators have both the ability to determine the buying positions and also the selling ones. Therefore, the purpose of this study is to build an intelligent algorithmic trading system based on various technical analysis indicators in the global gold market. In this research, an automated trading system using a genetic algorithm is presented and attemptswere made to optimize the settings of all the indicators, money management, profit target and stop loss limit, trading settings,etc.

The current study puts special emphasis on the issue of risk management, and through two different tools tries to manage the risk of the trading system. The structure of the article is as follows: the second part describes the genetic algorithm and the trading system. The third part elaborates on the results; and finally, in the fourth part, the conclusion is presented.

2. GENETIC ALGORITHM

First proposed by John Holland, the genetic algorithm is a way to find approximate solutions to optimization and search problems. An algorithm likewise is a special form of evolutionary algorithmthat uses evolutionary biology techniques such as inheritance and mutation. Obtaining the optimum answer in genetic algorithms requires the appropriate responses of a generation combined based on the principle of survival of the fittest in living organisms.

The genetic algorithm is constantly modifying the population of answers. At each stage, the genetic algorithm randomly selects people from the current generation as parents and brings them to create children who themselves are members of the next generation. Over successive generations, the population of answers "evolves" toward an optimum answer.

The main methods of genetic algorithms are designed to simulate the processes necessary for the evolution of natural systems.

For problem-solving,genetic algorithms simulate the principle of correct survival among members of a population over successive generations,each generation contains a population of characters and is similar to the chromosomes found in human DNA. Each person represents a point in the probe space and a possible solution. The members of each generation then enter into aprocess of evolution similar to that of living things.

Genetic algorithms behave similarly to the genetic structures and behavior of chromosomes in a population of individuals, using specific principles.

Once the first generation is randomly generated, the genetic algorithm will start evolving using 3 operators:

First, "SELECTION": Two parents are selected to mate and produce new chromosomes.

Second, "CROSSOVER": A new chromosome is created by the distribution of parental traits. Then, a location is randomly selected between string bits. Finally, the values of the two strings are moved together to the specified location:

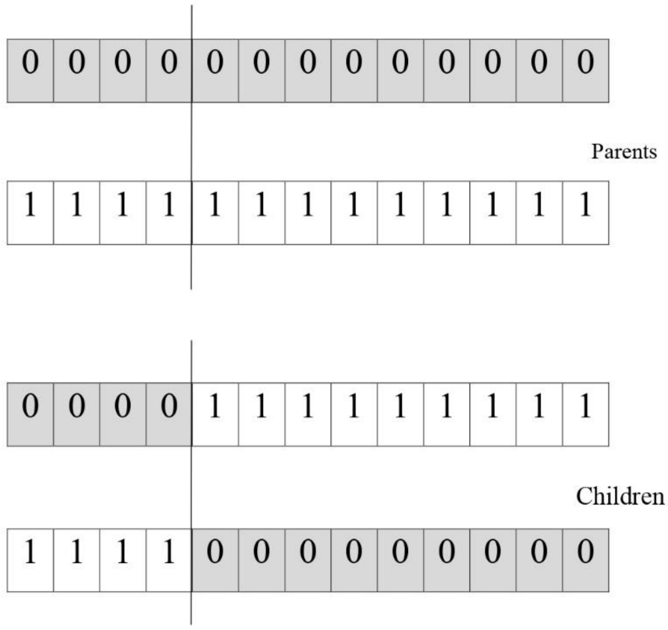

Fig. 1. Crossover Operation

Third,“MUTATION": corrections are randomly entered into the issue. With a very low probability, some bits of some parts of the new generation (children of the previous generation) will be changed. The goal is to maintain diversity among members of a population and prevent premature and incomplete convergence.

The mutation operator alone generates a random search in the probe space.

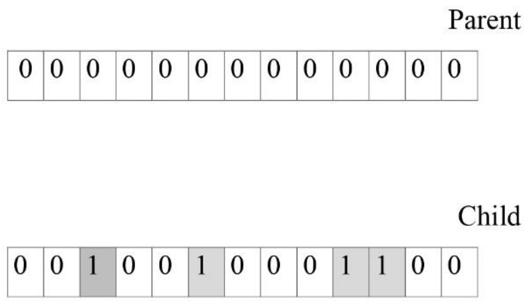

Fig. 2. Mutation Operation

The flowchart of the genetic algorithm is shown in Fig. 3.

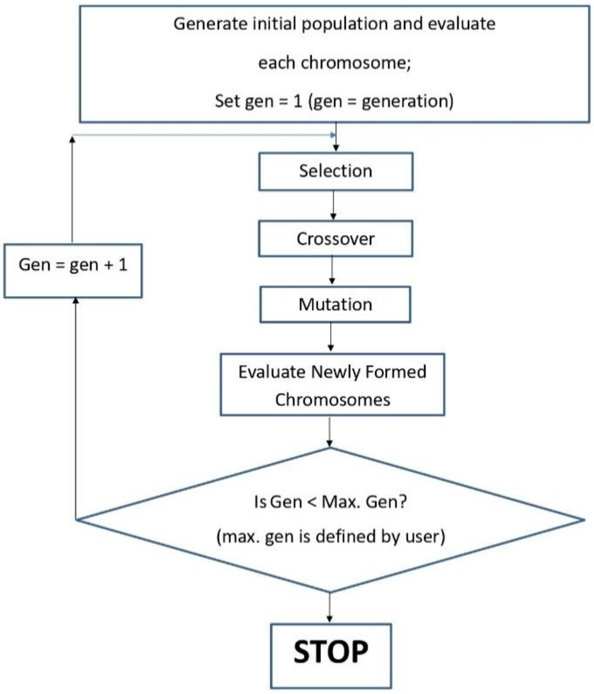

Fig. 3. Flowchart Genetic Algorithm

3. DATA USED

The high-quality global gold price data used in this research is provided in the form of tick data from DukascopyBank, from the following link:

https://www.dukascopy.com/trading-tools/widgets/quotes/historical_data_feed

After quality assessment for testing, the tick data for 18 years from 05/05/2003 to 01/10/2021, 6725 working days (433129560 units), UTC zone,were converted to 30-minute OHLC price bars, Including the opening price, the highest price, the lowest price, the closing price and the volume.All the tests were performed on the very same price bars.

4. RESULTS

The improved genetic algorithm is employed in the current study to obtain a strategy.Also, the concept of "fresh blood" has been discussed, which means when it is likely to be stuck in local optimality, fresh blood will be effective.Fresh blood is the random chromosomes that are replaced with the current generation chromosomes. The chromosomes by which being stuck in local optimality might happen are considered in combination with a weight to determine the optimum strategy of the fitness function.

On the current issue, each chromosome is a strategy and each chromosome gene is an indicator, signal, and trading condition.The two main operators of the genetic algorithm, intersection, and mutation, are applied to each chromosome and new strategies are created using them. The genetic algorithm used in this problem can be summarized in Figure 4.

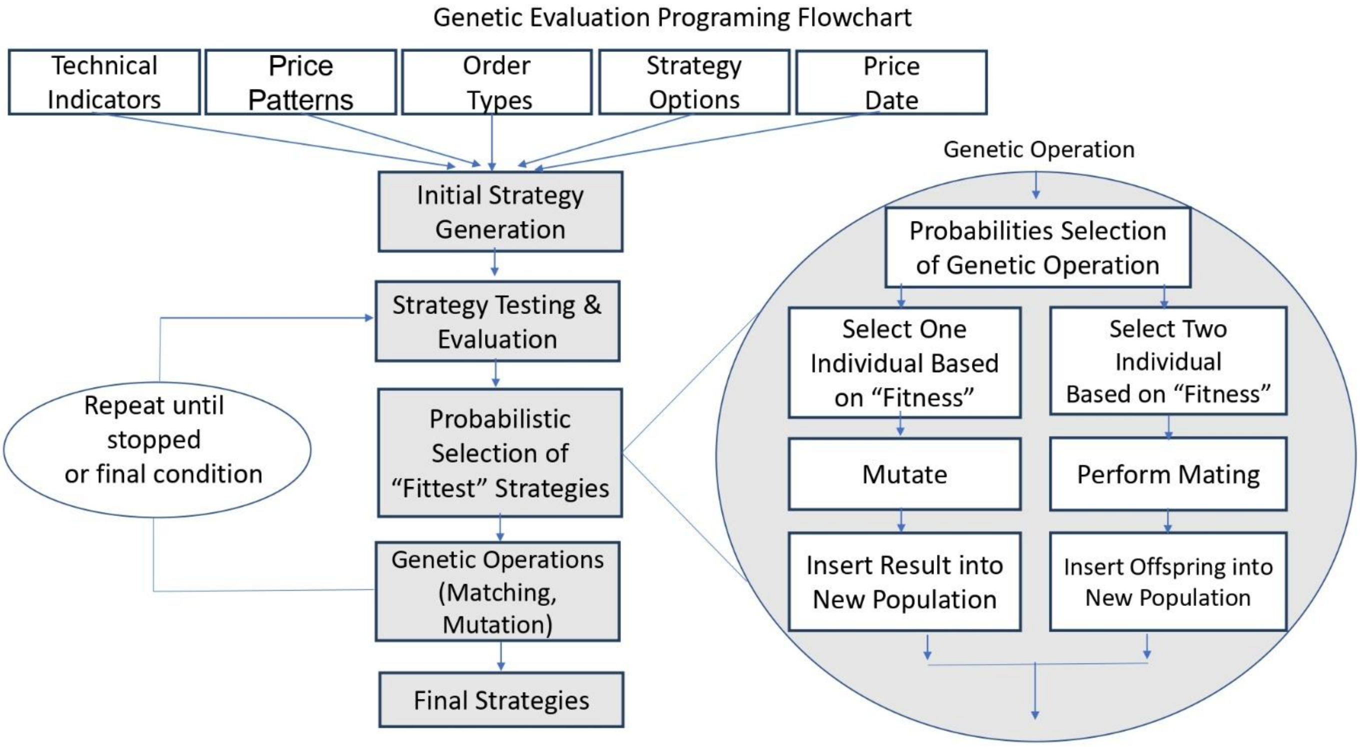

Fig. 4. Optimization Genetic Algorithm

As shown in Figure 4, each chromosome contains all the required information for each trading strategy, including indicators, trading settings, type of trade, entry and exit conditions, etc.

To compare the results obtained from the two strategies, the first one generated using a genetic algorithm and the second one generated randomly, the following criteria, shown in Table 1 will be used:

In this research, using genetic and random algorithms for each buy and sell on the historical gold price chart, the strategy is presented and finally, the best strategy produced in each category, which is selected according to the filters used, is compared. Two StrategyQuant platforms, version 129, were used to build strategies and create equalconditions on a computer with a 3.5 GHz processor, 8 cores, 12 Giga Bytes of memory, and both StrategyQuant platforms have been started togetherat the same time parallel. The job was finished simultaneously and the time given to each platform was 300 hours.

In this study, 256 indicators were used to receive the initial signal, 77 indicators and mathematical functions were also used to construct the indicators, 52 mathematical methods and formulas were used to provide the conditions for entering expected transactions, 4 entry methods and 8 exit methods with different combinations and settings. In all the strategies, the “fixed volume” method was used for money management.

Table 2. Result of GA and Random Algorithm

Name	Formula	Concept
# of *Trades*	–	Number of trades made in the whole test period
Return/DD Ratio	$\frac{\text{Net Profit (\$)}}{\text{MAX DD (\$)}}$	Ret/DDRatio
Net Profit	Total Profits – Total Losses	The profit of the strategy
Profit Factor	$\frac{\text{Gross Profit}}{\text{Gross Loss}}$	Profit factor
Stability	The square of R multiplied by the asset over time and the linear slope that connects the first transaction to the last one	Stability in taking profits
Stagnation	Days to reach the previous high in the equity curve	The strategy did not reach its previous high
Winning Percentage	$\frac{\text{\# of Wins}}{\text{\# of Wins} + \text{\# of Losses}}$	Winning trades percentage
Sharp Ratio	$\sqrt{252} \times \frac{\text{Avg (Daily Return\%)}}{\text{Std Dev (Daily Return\%)}}$	A measure of risk-adjusted return
Exposure	$\frac{\text{\# of Bars in all Positions}}{\text{Total Bars of the Period}} \times 100$	How much the system is at risk?
Gross Loss	The absolute value of total losses in losing transactions, excluding deposits and withdrawals	Sum of total losses
Gross Profit	The sum of the total profits in the winning trades without taking into account the deposits and withdrawals	Sum of total profits
SQN	$\frac{\text{Expectancy}}{\text{Std Dev (R Multiple)}}$	Strategy Quality Number (VanTharp)
CAGR		Compound Average Growth Rate

The settings for the strategy and genetic algorithm are as follows:

Crossing Rate: 93%

Mutation Rate: 30%

Initial Population: 400

Fresh Blood: 10%

	Genetic	Random
Number of Trades	6640	**538**
Ret/DD Ratio	50.55	**16.85**
Net Profit	5442.56 $	**999.47 $**
Profit Factor	1.77	**1.58**
Stability	0.89	**0.83**
Stagnation	236 Days	**1195 Days**
Winning Percentage	69.62 %	**54.46 %**
Sharp Ratio	4.45	**0.98**
Exposure	0.06 %	**5.13 %**
Gross Loss	7102 $	**1721.18 $**
Gross Profit	12544.56 $	**2720.65 $**
SQN	11.64	**0.39**
CAGR	36.19 %	**14.25%**

At the end of the process of building strategies, 40144781 strategies were made using the random method, of which 3334 were acceptable and 64825372 were made using the genetic method, of which 8324 were acceptable. Finally, the results were based on a genetic algorithm and strategy compared to the results obtained by the random method, and the results obtained are shown in Table 2.

Fig5compares the results of the strategy transactions for the two methods of the genetic and random algorithms.

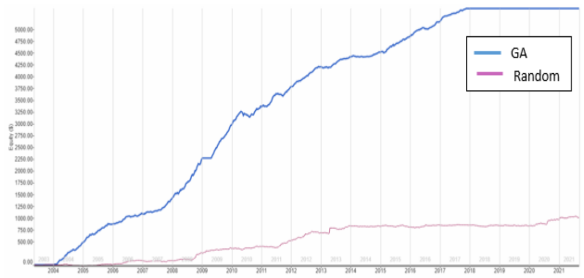

Fig. 5. Result of comparing GA and Random algorithm

5. CONCLUSION

In recent years,the use of artificial intelligence in financial markets, especially algorithmic trading has increased. In this research, it is tried to prove that by employing the genetic algorithm, it is more straightforward to achieve a strategyin a much shorter time and on equal termsto buy and sell gold; in which,compared to random generation, the number of trades throughout the test period, Ret/DD Ratio, net profit, profit factor, stability, winningpercentage, annual Sharperatio, SQN, and CAGR will increase, and stagnation, exposure, and total losses will decrease. According to the provided criteria, it has been proven that the strategy generated using the genetic algorithm is significantly superior, and the results indicate the superiority of the genetic method over the random.

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