Z E S Z Y T Y   N A U K O W E   P O L I T E C H N I K I   P O Z N A Ń S K I E J
Nr 83 Organizacja i Zarządzanie 2021

Joanna MAŁECKA*, Jorge VILA BIGLIERI**

THE SIMPLEST OPTION VALUATION GENETIC ALGORITHM MODEL – NASDAQ CASE STUDY

DOI: 10.21008/j.0239-9415.2021.083.04

The capital market is the meeting place of supply and demand. The profit orientation possible through the stock market stimulates two processes: 1) buying or 2) selling financial instruments – a long or short option. Investing is a process accompanied by fluctuations – often of <1% per day. Hence, individual investors look for alternatives, which include derivatives that fluctuate up to 100% per day. Therefore, the need was perceived to develop an instrument – a valuation tool – to help individual investors make investment decisions. The Black-Scholes Model (BSM) uses six independent variables. It was therefore decided to compile an alternative valuation model based on the Genetic Algorithm (GA) on the strength of companies listed on NASDAQ: FaceBook, Apple, Amazon, Netflix and Google (so-called FAANG companies), using Eureqa GA software. The purpose of this paper is to present the results of a study that attempts to develop a more efficient option pricing model by comparing the accuracy of the Genetic Algorithm (GA) and the Black-Scholes Model (BSM) and evaluating gaps in underlying price movements. The comparison of the genetic algorithm with the traditional Black-Scholes option pricing model led to the development of a new linear investment model – investors can make predictions using one variable – the share price, which should significantly optimise strategic investment decisions. The presented model is characterised by higher investment efficiency, especially important for individual investors, who usually are not able to achieve the profit scale effect based on the value of a retail investment portfolio.

Keywords: NASDAQ, options, genetic algorithms, stock market, Black-Scholes model

* Politechnika Poznańska, Wydział Inżynierii Zarządzania, Instytut Zarządzania i Systemów Informacyjnych, Zakład Przedsiębiorczości i Komunikacji w Biznesie. ORCID: 0000-0002-5017-0417.

** Economics and Accounting Department, University of Vigo, Spain. ORCID: 0000-0002-7684-4096.

1. INTRODUCTION

Warren Buffett calls derivatives 'financial weapons of mass destruction'. He criticizes the Black-Scholes options price model in a letter send to Berkshire Hathaway's shareholders in 2002 using an example based on Costco with an "insane" distortion. This commentary is an incentive to start developing new, accurate and simpler models worldwide (Black, Scholes, 1973, p. 637-654; Buffet, 2002).

Further, options have changed since 1973. Nowadays, most traded options are short term ones, with a strike price closer to the underlying price. The introduction of high frequency trading as well as huge price movements (volatility) also play an important role. This issue generated a new line of investigation to improve option valuation (Bradford, 2010, p. 107-111). Options became popular because paying a lower price gives the opportunity to earn several times the money invested (the contract price is called a premium), without assuming any financial responsibility beyond the premium. Besides, you can buy options for expanding (Bull) or declining (Bear) markets. Moreover, American Broker Commissions are low.

Options are derivatives whose value mainly depends on the price of the underlying asset. An option is a contract that gives the owner the right, but not the obligation, to buy (call option) or sell (put option) the underlying asset at a strike (the given price) on a given expiration date in the future. There are two option types: American options have the right, but not the obligation, to cancel the contract anytime, but European options do not have this right. Most traded options worldwide are American options. In any case, alternative securities market opportunities should be considered an efficient source of financing (Małecka, 2017a, p. 34-43; 2017b, p. 393-401; 2016, p. 11-24).

Trading options are a zero-sum game – for any buyer's profit, there are seller's losses. The trading language has its own words, such as long – when investors buy an option, and short one – when the sell transaction takes place. With these four bricks (long call, long put, short call and short put), and with different strikes and different expiration dates, several scenarios may be constructed to analyse the risk and the profitability in a given market situation. When an underlying asset price moves, an army of trading operations (more robot than human) moves the options price properly into a new equilibrium.

The purpose of this paper is to present the results of a study that attempts to develop a more efficient option pricing model by comparing the accuracy of the Genetic Algorithm (GA) and the Black-Scholes Model (BSM) and evaluating gaps in underlying price movements.

This paper presents the results of a study on combining the genetic algorithm (GA) branch of artificial intelligence (AI), with options derivatives in a simple way to be applied to the quotes of companies: Facebook, Apple, Amazon, Netflix and Google (FAANG), the fastest growing on the National Association of Securities Dealers Automated Quotation (NASDAQ). NASDAQ is suitable for analysing the multivariate behaviour of options of this type (Vila Biglieri, Malecka, 2019, p. 81-101). A simplification is to select only the most relevant variable for option pricing. July 7, 2021 was chosen as the random day. The valuation of the GA model was estimated using Eureqa Software, through which its accuracies were compared with the BSM option pricing model.

2. THE ROLE AND IMPORTANCE OF THE GENETIC ALGORITHM & BSM IN OPTION PRICING

The first neural network (NN) document was related to medical electronics (Martin, 1956, p. 47). Years later, the mathematics and medical background was created (Shipley, 1966, p. 365; Griffith, 1966, p. 350-354). In this early era, there was a lack of processing power and storage. However, both aspects were improving and ultimately became available to investigators. J.H. Holland is considered the Genetic Algorithms (GA) pioneer (Holland, 1975). The first financial NN article was published in January 1993 and compared discriminant analysis with artificial neural networks by Y.O. Yoon, G. Swales and T.M. Margavio (Yoon, Swales, Margavio, 1993, p. 51-60). Two more articles were published in that same year on financial distress patterns using NN and multilayered backpropagation for finance analysis (Coats, Fant, 1993, p. 142-155; Chang, Sheu, Thomas, 1993, p. 11-15).

J.M. Hutchinson and his scientific team were considered pioneers in option pricing using learning networks (which until today is called neural networks) (Hutchinson, Lo, Poggio, 1994, p. 851-889). Some years later, S.H. Chen and W.C. Lee started using a GA to price options. At the beginning of the XX century, the cost reduction in data storage and technology made AI and big data available to financial researchers (Chen, Lee, 1997, p. 110-115; Yao, Li, Tan, 2000, p. 455-466).

Artificial intelligence has continued to develop NN using machine learning (ML). Today, ML is a promising field for improving the BSM, predicting and forecasting the cryptocurrency index predicting bank insolvency and providing a Foreign Exchange[1] (FOREX, FX) visual analysis, starting a new promising branch called financial vision (Chowdhury, Mahdy, Alam, 2020; Karacor, Erkan, 2020, p. 61-76; Petropoulos, Siakoulis, Stavroulakis, 2020, p. 1092-1113; Chowdhury, Rahman, Rahman, 2020). Currently, NN analysis is based on evolutionary computation,

[1] Forex, FX – an over-the-counter foreign exchange market in which banks, large international corporations, governments, central banks and institutional investors from around the world carry out currency exchange operations 24 hours a day using telephone networks, IT connections and information systems.

within which GAs are the most prominent example. The GA tries to solve a problem as nature does, finding a function that reduces the mean absolute error (MAE) between input and output data (Mitchell, 1996).

Artificial intelligence is fighting to win against the human brain. One typical way in which this battle is fought is through challenging games, where NNs were designed to win against humans – as humans are slow compared to computers, to the next step which consists of playing machines against machines (self-play) to increase learning speed (Yuandong, Ma, Gong et al., 2019; Silver, Hubert, Schrittwieser et al., 2018, p. 1140-1144; Silver, Hubert, Schrittwieser et al., 2017; Silver, Huang, Maddison et al., 2016, p. 484-503).

Promising GA financial applications are trading systems with multiple kernel adaptative filters, producing profits from market instability with Robo-Advisors, creating a dynamic guaranteed option hedge system and the GA application for the German market to calculate option prices as an alternative to the BSM (Huang, Chiou, Chiang et al., 2020; Ahn, Lee, Ryou, 2020; Herzog, Osamah, 2019; Song, Han, Jeong, 2019).

From the financial perspective, option pricing is one of the most challenging problems in financial engineering and the aim of this article. The Chicago Board Options Exchange (CBOE), which opened in April 1973, represents the ideal place to study options. By June 2000, the total notional amount of derivatives worldwide was the equivalent of $18 000 for every person on Earth (MacKenzie, Millo, 2003, p. 107-145).

The theory of option pricing developed by F. Black and M. Scholes in 1973 and then by R.C. Merton in 1976 was a crucial breakthrough, bringing Scholes and Merton the 1997 Nobel Prize[2]. The BSM is the most frequently used option price valuation model. This model assumes no transaction cost, market efficiency, no dividends, constant volatility and a risk-free interest rate. Additionally, stock behaviour should follow a Brownian motion.

The BSM for a European call option is formulated as follows (1):

$$\mathrm{C = St\,N(d1) - K\,e^{-rt} N\,(d2)} \tag{1}$$

Formula 1. European Call Option Formula

A European put option is formulated as follows (2):

$$\mathrm{P = -St\,N(-d1) + K\,e^{-rt} N\,(-d2)} \tag{2}$$

Formula 2. European Put Option Formula

where: $\mathrm{d1} = \frac{\ln\frac{S}{K} + (r + \frac{\delta_v^2}{2})\,t}{\delta_s \sqrt{t}}$ and $\mathrm{d2} = s1 - \delta_s \sqrt{t}$

[2] F. Black died in 1995.

Abbreviations stand for:
C – call option price,
P – put option price,
S – current stock price,
K – strike price,
r – risk-free interest rate,
t – time to maturity,
N – normal distribution.

The BSM has been updated by several authors from all over the world, among others: H. Zhang, F. Liu, R.G. Batogn, A. Atangana. Currently, the BSM is a reference, but investigators are developing new pricing and forecasting models to reduce risk and increase profitability. By researching the French market, a deviation was identified between market price and BSM estimation. In this case, based on empirical evidence, G. Bakshi, C. Cao and Z. Chen have found it necessary to include stochastic volatility in the BSM which has been used in the presented research results (Zhang, Liu, Turner, 2016, p. 1772-1783; Batogna, Atangana, 2019, p. 435-445; Aboura, 2013; Bakashu, Cao, Chen, 1997, p. 2003-2049).

3. METHODOLOGY

The purpose of the research results presented in this paper is to evaluate the effectiveness of BSM option pricing and the GA model for FAANG companies. Thus, an attempt was made to develop a model helpful in measuring, forecasting and modelling the volatility of financial instrument prices. The BSM model assumes that options are not independent instruments and can be replicated using simpler assets. Genetic algorithms, on the other hand, are based on searching the space of alternatives in order to find the optimal solution.

The initial hypothesis was to find similarities between the normalised price of the underlying and the price of a call option (with an exercise date closer to the price of the underlying and an expiry date of the nearest Friday). The hypothesis is to develop the simplest pricing model using changes in option and underlying prices, starting with a call option (fig. 1).

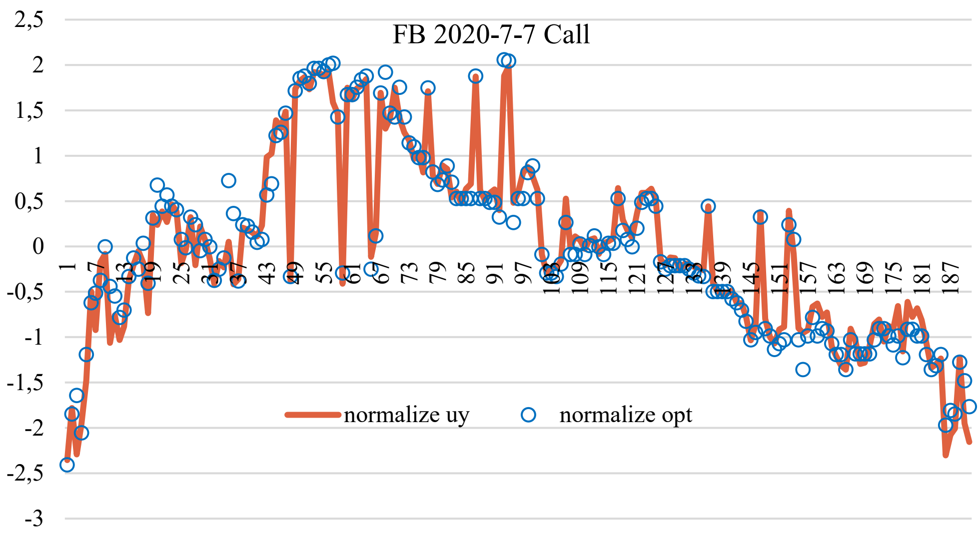

Fig. 1. Normalized Call and underlying prices

It should be noted how some call prices are outliers. Options prices overreact on the underlying price movements as it can be observed at 35 data (up FB price) and 155 data (down FB price) (fig. 2).

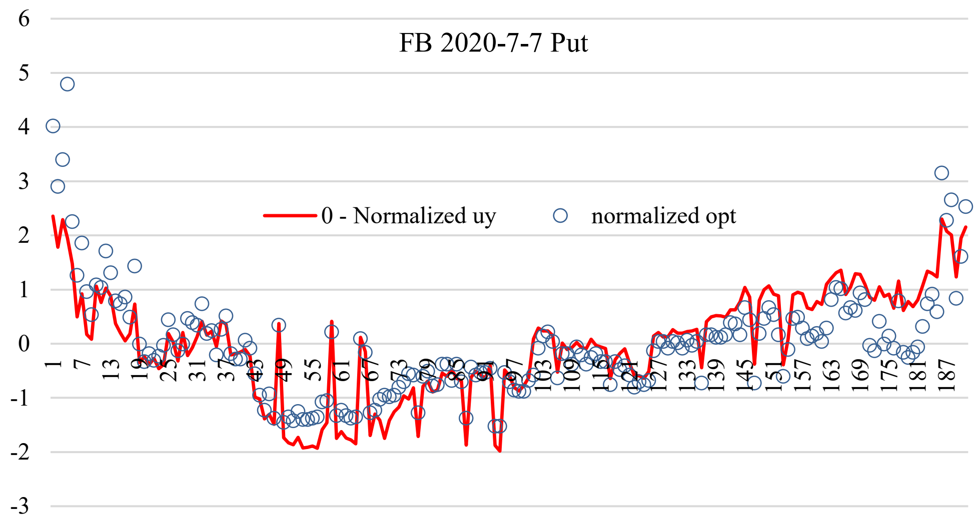

Fig. 2. Normalized Put and Zero – Normalized underlying prices

In order to compare normalized, standardised underlying prices are required. The inversion consists in subtracting normalized underlying prices to zero. Appreciation requires the Put prices to be less accurate than Call prices. The initial distortion is generated by a AAPL bear market on the previous day, which raises the put prices. At opening, put prices are adjusted quickly, keeping slightly over the inverted normalized price till midsession, falling below the inverted underlying price almost to the session end, with a relevant rebound in the last trading minutes.

Financial markets generate a huge quantity virtue of data. Interactive Broker's API delivers data every 200 milliseconds. Nevertheless, the two-minute period is selected to have graphs which can be printed on a paper. The database consists of more than 300 000 call and put option observations which contains the underlying price, one standard deviation option strikes, expiration dates, ask, bid, last, volume, the Interactive Brokers (IB) model, maximum, minimum, news, etc.[3]. In this study, the IB information model, which is the best estimation of the BSM, was adopted as it is specifically designed for American options, using the U.S. interest rate and best guess dividend payment schedule based on historical data.

The NASDAQ[4] is open from 9:30 to 16:00, Eastern Standard Time, for a total of 390 minutes. At a given moment (07-14 at 19:40:14) it's possible to download 1862 stock and option prices every 2 minutes – in this way Apple stock quotes and its options have been presented as a static graph (AAPL) (fig. 3).

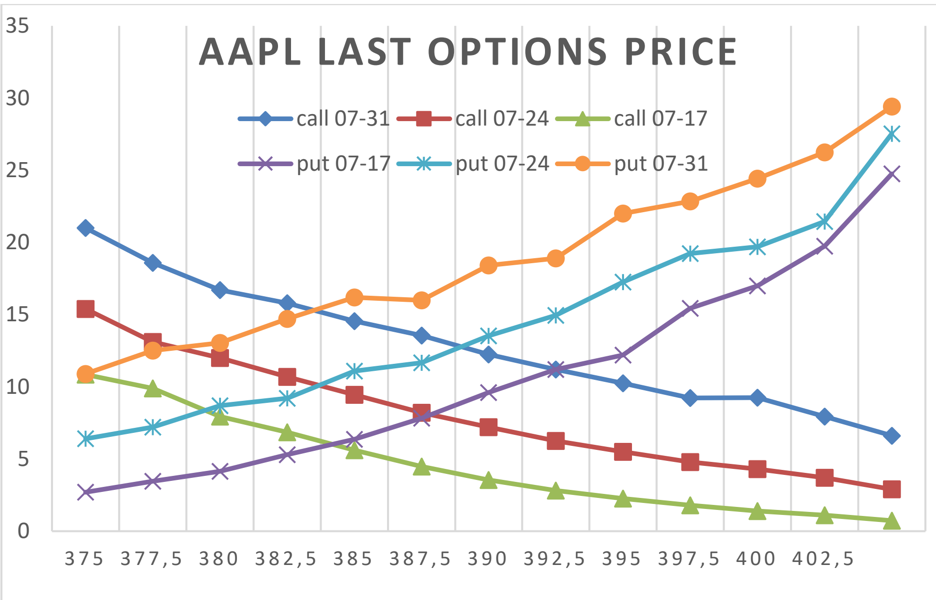

Fig. 3. Bidimensional graph with last option prices by strike and expiration date

[3] Data provided by Interactive Brokers (interactivebrokers.eu/es/home.php, 29.08.2021).

[4] The NASDAQ Composite is a stock index calculated on the US NASDAQ stock exchange which for the first time exceeded the level of 1000 points on July 17, 1995. On March 10, 2000, it reached the level of 5132.52 points, signalling the peak of fascination with shares of IT companies, including internet companies.

It deserves emphasis how call prices are lower as the strike increases and are higher with longer expiration dates. Call and put price cut between 382.5 and 385 – in other words, call and put-prices cross on the underlying price. 07-24 Call and Put intersection is displaced slightly to the right and the 07-31 intersection slightly more, indicating a growing market expectation for the AAPL price.

Option prices are smooth when they are closer to the expiration date and the underlying price. The importance of the line marked in a dark blue should be emphasized (put 07-24) because it has a lower point on 402.5, almost touching the yellow line (put 07-31) (see fig. 3). As the market is betting on raising AAPL prices, the market is avoiding trading puts. This 402.5 price is obsolete, but bid and ask prices have corrected the gap, making it impossible to buy at this lower price. Next trade will correct this put last price. To improve visualization the same information has been analysed in a three-dimensional image (fig. 4).

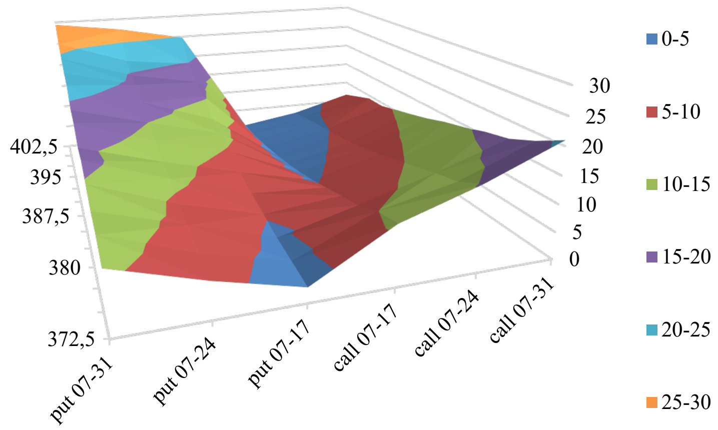

Fig. 4. 3-Dimensional graph with last option prices by strike and expiration date

In this article, a dynamic approach is required to set the GA models. Taking data every two minutes will produce 195 observations per business day. The model studied 959 observations, an average of 191.8 observations per company due to some data are lost because there is no last option price until the first option transaction after the market opening.

The Eureqa[5] software processes the information and generates GA sequential solutions, increasing the size[6] to obtain the global optimum model, defined as the model with the smallest MAE. To simplify this model, all the BSM variables have been checked (underlying price, strike, expiration date, volatility, risk-free interest

[5] Nutonian is the creator of the Eureqa software and was bought by the DataRobot Company (www.nutonian.com/products/, 29.08.2021).

[6] Size is the number of formula components.

rate and dividend yield) to find the most relevant variable. Simplification was achieved in the following steps:

- the FAANG do not pay dividends, so dividends were excluded,
- to explain options price changes, so the risk-free interest rate was excluded,
- on the NASDAQ, the main option volume is from options with the strike closer to the underlying price and with the next Friday expiration date; the most traded options have been checked, ensuring liquidity and performance; in this way, data from strikes and expiration dates were excluded from the model.

By carrying out further research by way of further simplifications, the last price is selected as the most relevant variable to explain options price. Ask and bid prices are not real prices because a price must be born from an interchange between sellers and buyers.

The methodology presented in the article is inspired by Herzog and Osamah, who applied the GA to the German market to compute option prices, compared it to the BSM and found that the GA had a smaller MAE on the market price, demonstrating that the GA model outperforms the BSM (Herzog, Osamah, 2019).

Therefore, it was introduced in the research methodology following improvements which the main assumptions concerned:

- applying the GA model to the American market only,
- developing a valuation model using the underlying price to evaluate the option price for FAANG companies.

The randomly selected day was Tuesday, July 7, 2021; the put and call options selected were those with strike prices closer to the opening price and next Friday expiration date, four days before their expiration date (tab. 1).

Table 1. Data of selected companies, opening prices and variation

		Sample (07-07)	
Name	Ticker	Opening price	Put & call strike
niFacebook	FB	239.08	240
Apple	AAPL	375.12	375
Amazon	AMZN	3 042.59	3 040
Netflix	NFLX	496.34	500
Google (Alphabet)	GOOGL	1 496.87	1 500

The Eureqa searches for the global optimum using the following the GA Valuation Model formula (3):

$$\begin{gathered}\mathrm{Last\_call\_price}_n^{7th} = f(\mathrm{Last\_underlying\_price}_n^{7th}) \\ \mathrm{Last\_put\_price}_n^{7th} = f(0 - \mathrm{Last\_underlying\_price}_n^{7th})\end{gathered} \tag{3}$$

Formula 3. GA Valuation Model

The values and presented research results were achieved by introducing the following steps to the methodology:
- accessing the database to retrieve FAANG information (underlying last price, call last price, put last price and the BSM data),
- generating a table with the underlying price of the t period,
- uploading the table to Eureqa, allowing for the use of exponential and logarithm tools to improve accuracy.

4. RESULTS

To receive the estimates and research results presented in the article, as well as all samples to evaluate the option price as a linear function of the underlying, the data from July 7th was used. By carrying out calculations in accordance with the methodology presented earlier, two models are required – one for call options and the other for put options.

4.1. GA Valuation Model Call (GAVMC)

Eureqa was run to estimate GAVMC, and the equation for the simplest (size = 5) and best linear function with the lower MAE was found, and the formula consist of LCP_n^{7th} (4).

$$\mathrm{LCP}_n^{7th} = 0.926645053709684\,\mathrm{LUP}_n^{7th} - 0.0228446942131238 \tag{4}$$

Formula 4. LCP_n^{7th} Model Value

This is the simplest model and has a surprising accuracy. It has an R^2 of 0.91781811 with an MAE equal to 0.075100222 and a mean square error (MSE) equal to 0.17424785. The Eureqa software was stopped because with an increasing complexity it was unable to achieve a relevant MAE reduction and what is presented in the graph represents GAVMC and call last prices (fig. 5).

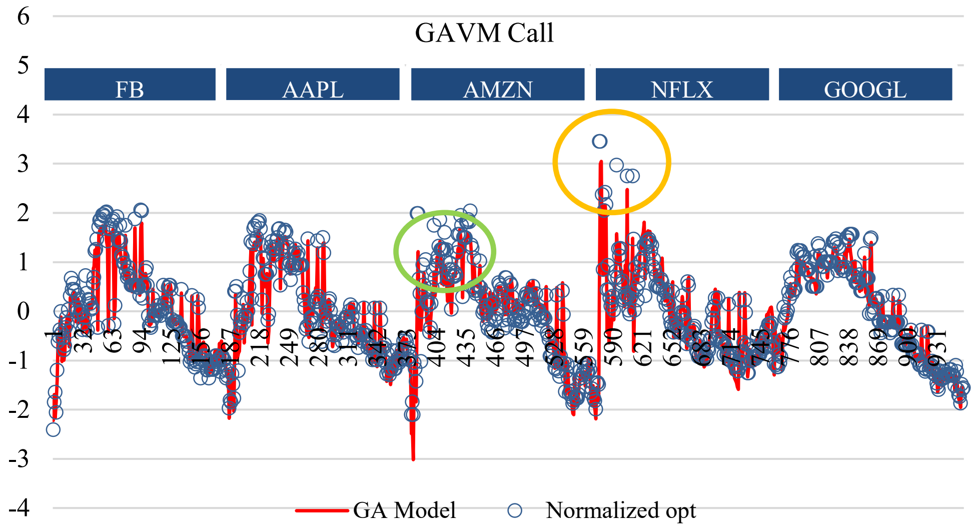

Fig. 5. GA Valuation Model Call

Two zones were highlighted (green and the yellow circles in fig. 5). The green zone has some AMZN call option prices (blue circles) that are unfitted by GAVMC (red lines). In the yellow zone, there are 5 unfitted blue circles with a higher deviation.

The most realistic interpretation of the green zone is that the market was expecting an increase in AMZN share prices in the first session quarter, but this expectation disappears. The same reasoning can be used to explain NFLX based on higher underlying price growth. This kind of market behaviour is based on option prices that depend on the offer and demand. When an underlying price goes up, a huge demand with a normal offer will produce a price increase that must be paid by the buyers if they want to make the deal (tab. 2).

Table 2. Comparing the BSM and the GAVMC Call

Call Value	Option price ($)	MAE	MSE	Observations
Avg. Market value call	16.9101			959
Avg. BSM value call	15.9219			959
Avg. GA-value call	16.7764			959
Market vs. BSM call	0.9882	1.7187	8.5768	959
Market vs. GA call	0.1333	0.6334	1.6802	959

The data analysis showed the market average minus BSM average (0.9882), greater to market average minus GAVMC average (0.1333). Both average comparisons are significant in the contrast test. Checking the GAVMC with Market MAE equal to 0.6334 was found. Comparing with the BSM and Market, the MAE is 1.7187, more than twice the GAVMC result. The MSE difference between the two models is astonishing, and GAVMC is more than 5 times more accurate than BSM. The sign test – comperition increases and decreases on option price with changes in the BSM or GA model – analysis reveals GAVMC price and call option changes in the same direction 716 times of 959 observations (75.66%) while BSM call only changes 519 times (54.12%).

4.2. GA Valuation Model Put (GAVMP)

The Eureqa finds the best linear function equation for GAVMP with a lower MAE, in the way of following LPP_n^{7th} with the equation (5):

$$\mathrm{LPP}_n^{7th} = -\,0.938619752602708\,\mathrm{LUP}_n^{7th} - 0.0377854933228916 \quad (5)$$

Formula 5. LPP_n^{7th} Model Value

Again, its accuracy is slightly better than GAVMC, R^2 is 0.93714964, the best model finds a slightly higher MAE (0.12170196), and MSE is 0.24866046.

To understand the model, a graphical representation has been presented and analysed. It is worth emphasizing that there is a tendency in which the graph is similar to an inverted figure 3 because puts have axis symmetry (fig. 6).

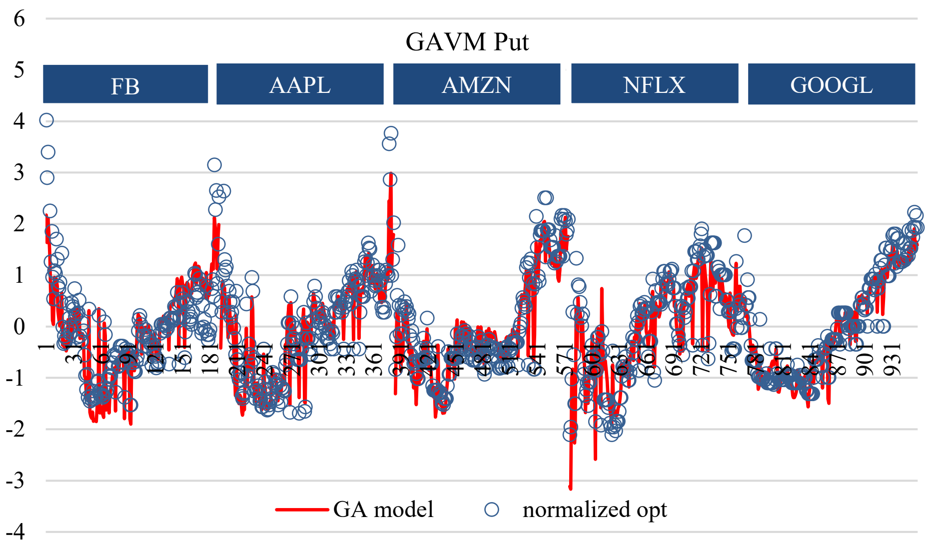

Fig. 6. GA Valuation Model Put

At the beginning of the session, the huge unfitted option prices has been observed, especially on FB and AMZN. Possible explanations for GAVMP valuation differences are as follows:

1) most of the outliers appear at the opening: this is well known effect – put option opening price variations are greater than those of call variations on most trading days;
2) theoretically, put and call contracts are symmetrical; on paper, traders' behaviour has less tolerance for losses than profits – the traders are in a different mental disposition when they are buying puts than when they are buying calls;
3) there are common trader expressions: stock prices walk up the stairs slowly and down by elevator quickly (Lasvignes, 2020); it never rains but it pours; when stock falls, it falls quickly; the demand for put options increases quickly and prices grow exponentially; this rising price must be paid by those who are looking get in the business;
4) at the session middle, on the FB, AAPL and NFLX bottom, some unfitted low put prices can be found.

In this case, as owners are not keen to accept losses, they wait for another underlying price change, which explains why the call model prices are lower than call prices (tab. 3).

Table 3. Comparing the BSM and GAVM Put

Market value	Option price ($)	MAE	MSE	Observations
Avg. Market value put	15.5586			959
Avg. BSM-value put	14.9869			959
Avg. GA-value put	14.9931			959
Market vs. BSM put	0.5717	1.2507	5.1563	959
Market vs. GA put	0.5655	1.0652	2.6013	959

Sign Test performance supports that the GAVMP has better performance with 70.59%, while BSM STP has 54.64%. As the conclusion the summarize the relevant parameters of each model and application was received (tab. 4).

Table 4. All parameters statement

MODEL	GAVMC valuation	GAVMP valuation
R^2	0.9178	0.9371
Model MAE	0.0751	0.1217
Model MSE	0.1742	0.2487
Market vs. BSM averages ($)	0.9882	0.5717
Market vs. GA averages ($)	0.1333	0.5655

tab. 4 cont.

MODEL	GAVMC valuation	GAVMP valuation
Market vs. BSM MAE	1.7187	1.2507
Market vs. GA MAE	0.6334	1.0652
Market vs. BSM MSE	8.5768	5.1563
Market vs. GA MSE	1.6802	2.6013
Market vs. BSM STP*	54.12%	54.64%
Market vs. GA STP	75.66%	70.59%

* Stands for sign test performance.

By obtaining accurate values of the GAVMC valuation and GAVMP valuation, any potential investor can apply the finished model based on the presented values of each test. In this way, by combining the genetic algorithm with the traditional Black-Scholes option pricing model, a new linear investment model has been developed, one that allows investors to make predictions using only one variable – the share price, which should significantly optimise strategic investment decisions.

5. CONCLUSION

The stock market is dependent on a wide range of variables, some of them highly unpredictable (nowadays mostly e.g.: COVID-19 and its subsequent permutations, Cryptos, Donald Trump's tweets, Presidential Elections, Brexit updates). Traders understand such dynamism is part of the experience. In one sentence, trading is enjoyable and only sometimes money can be made.

The data presented in this paper are the results of research on the main contributions:

- the value of the GA model with linear equations, which can valorise option prices with overall better performance than the BSM model,
- commenting and graphically presenting some practical aspects of trading.

FAANG's options are successfully valuated with the GAVMC and GAVMP based on the following evidence:

- GA models have an R^2 coefficient higher than 90%,
- the average difference between Market vs. BSM vs. GA is always lower in GA models – the contrast test checks averages and concludes they are significantly equal,

- MAE and MSE models are lower as valuation models and higher as prediction and validation models,
- a comparison of market prices with the BSM and GA models gives the result: the MAE is always better for GA models than for the BSM, supporting the use of linear equations for valuation,
- sign Test Performance (STP) has better performance on GA models than BSM.

Option prices depend on the offer and demand. When an underlying price goes up quickly, a high call demand will produce a huge call price increase. This can be paid by the buyers if they want to join the business. Buyer and seller behaviour (robot or human) is impossible to predict in a mathematical way at a given moment. This conclusion supports the notion that sometimes reality is unpredictable – the market has its own life. Beginners think it will be easy to win money at the stock market, but normally, they find the opposite to be true. Broker ads reveal that more than 70% of its investors lose money. The market belongs to experienced investors who know their own way to trade. Hence, any research or publication to disseminate financial knowledge that helps in making decisions is significant and serves to ensure that inexperienced people do not lose money.

Currently, the market has plenty of high frequency traders (HFT) who can make decisions in milliseconds, paying big money to have their servers some metres closer to the clearing house to save precious milliseconds. This advantage allows them to know when somebody places a buying order, buy the open positions, increase the price on available orders one or two cents and close the order with a slight profit multiplied by a million daily operations. At the end of the day, HFT close all operations. Due to concern about this lack of ethics, IEX created a fair clearing house. They solve the speed differences using 60 kilometres of optic fibre to force everybody to have similar trading delays. However, traders care less about this, and they trade on IEX as well as on other clearing houses.

Trading on the exchange is accompanied by buying pressure, which, especially when the price of the underlying instrument rises rapidly, causes perturbations in the quotations. The presented model is characterised by higher investment efficiency, especially important for individual investors, who usually are not able to achieve the effect of profit scale based on the value of a retail investment portfolio.

Despite the many demonstrated results, it is desirable to undertake more trials to compare this GA solution over broader periods and in broader markets to increase the accuracy of the learning-by-doing approach, which points to a further direction for research.

BIBLIOGRAPHY

Aboura, S. (2013). Empirical performance study of alternative option pricing models: An application to the French option market. *Journal of Stock Forex Trading*, 2, 1-10.

Ahn, W., Lee, H.S., Ryou, H. (2020). Asset allocation model for a Robo-advisor using the financial market instability index and genetic algorithms. *Sustainability*, 11(15), 4100.

Bakshi, G., Cao, C., Chen, Z. (1997). Empirical performance of alternative option pricing models. *Journal of Finance*, 52, 2003-2049.

Batogna, R.G., Atangana, A. (2019). Generalised class of time fractional Black Scholes equation and numerical analysis. *Discrete and Continuous Dynamical Systems-Series S*, 12(3), 435-445. Retrieved from: https://doi.org/10.3934/dcdss.2019028.

Black, F., Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, 81, 637-654.

Bradford, C. (2010). Warren Buffett, Black-Scholes, and the valuation of long-dated options. *Journal of Portfolio Management Summer* 2010, 36(4), 107-111. Retrieved from: https://doi.org/10.3905/jpm.2010.36.4.107.

Buffett, W. (2002). *Berkshire Hathaway Annual Financial Report*, 16. Retrieved from: https://www.berkshirehathaway.com/2002ar/2002ar.pdf.

Chang, C.F., Sheu, B.I., Thomas, J. (1993). *Multilayered backpropagation neural networks for finance analysis. World Congress on Neural Networks (WCNN 93, Portland), Portland, July 11-15*.

Chen, S.-H., Lee, W.-C. (1997). *Option pricing with genetic algorithms, Separating out-of-the-money from in-the-money*. Paper presented at the IEEE International Conference on Intelligent Processing Systems, Beijing, China, October 28-31, 110-115.

Chowdhury, R., Mahdy, M.R.C., Alam, T.N. (2020). Predicting the stock price of frontier markets using machine learning and modified Black-Scholes option pricing model. *Physica A: Statistical Mechanics and its Applications*, 555, 124444.

Chowdhury, R., Rahman, M.A., Rahman, M.S. (2020). An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning. *Physica A-Statistical Mechanics and Its Applications*, 551, 124569.

Coats, P.K., Fant, L.F. (1993). Recognizing financial distress patterns using a neural-network tool. *Financial Management*, 22(3), 142-155.

Griffith, J.S. (1966). Modelling Neural Networks By Aggregates Of Interacting Spins. *Proceedings of The Royal Society* of London Series A-Mathematical And Physical Sciences, 295, 1442, 350-354.

Herzog, B., Osamah, S. (2019). Reverse engineering of option pricing: An AI application. *International Journal of Financial Studies*, 7(4), 68.

Holland, J.H. (1975). *Adaptation in Natural and Artificial Systems*. Ann Arbor: The University of Michigan Press.

Huang, S.C., Chiou, C.C., Chiang, J.T., Wu, C.F. (2020). A novel intelligent option price forecasting and trading system by multiple kernel adaptive filters. *Journal of Computational and Applied Mathematics*, 369, 112560.

Hutchinson, J.M., Lo, A.W., Poggio, T. (1994). A nonparametric approach to pricing and hedging derivative securities via learning networks. *Journal of Finance*, 49, 851-889.

Karacor, A.G., Erkan, T.E. (2020). Exploiting visual features in financial time series prediction. *International Journal of Cognitive Informatics and Natural Intelligence*, 14(2), 61-76.

Lasvignes, C. (2020). Radio program emitted July, 8th. *Tiempo de inversión*. Radio Intereconomía. Retrieved from: https://intereconomia.com/directo.

MacKenzie, D., Millo, Y. (2003). Constructing a market, performing theory: The historical sociology of a financial derivatives exchange. *American Journal of Sociology*, 109(1), 107-145. Retrieved from: https://doi.org/10.1086/374404.

Małecka, J. (2017a). Regulation of the Warsaw Stock Exchange: History and Operating Rules. *Journal of Economics World*, 5, 1, 34-43. Retrieved from: http://dx.doi.org/10.17265/2328-7144/2017.01.004.

Małecka, J. (2017b). Alternative Securities Markets as Financing Sources for SMEs – Selected Aspects of AIM and NC. *Contemporary Issues in Business, Management and Education*, 393-401.

Małecka, J. (2016). Alternative Securities Markets in Poland and the United Kingdom. *Problemy Zarządzania*, 14, 4(63), 1, 11-24. Retrieved from: http://dx.doi.org/10.7172/1644-9584.63.1.

Martin, N.M. (1956). On the role of neural network models. *IRE Transactions on Medical Electronics*, 7, 47.

Merton, R.C. (1976). Option pricing when underlying stock returns are discontinuous. *Journal of Financial Economics,* 3, 125-144.

Mitchell, M. (1996). An introduction to genetic algorithms. Complex Adaptive Systems. Cambridge: MIT Press.

Petropoulos, A., Siakoulis, V., Stavroulakis, E. (2020). Predicting bank insolvencies using machine learning techniques. *International Journal of Forecasting*, 36(3), 1092-1113.

Shipley, T. (1966). Mach bands: Quantitative studies on neural networks in the retina. In: F. Ratliff (Ed.) (p. 365). Holden-Day.

Silver, D., Huang, A., Maddison, C.J., Guez, A., Sifre, L., van den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature*, 529, 484-503.

Silver, D., Hubert, T., Schrittwieser, J., Antonoglou, I., Lai, M., Guez, A., Lanctot, M., Sifre L., Kumaran, D., Graepel, T., (2018). A general reinforcement learning algorithm that masters Chess, Shogi, and Go through self-play. *Science*, 362, 1140-1144.

Silver, D., Hubert, T., Schrittwieser, J., Antonoglou, I., Lai, M., Guez, A., Lanctot, M., Sifre, L., Kumaran, D., Graepel, T. (2017) Mastering Chess and Shogi by self-play with a general reinforcement learning algorithm. *Computer Science*.

Song, H., Han, S.K., Jeong, S.H., (2019). Using genetic algorithms to develop a dynamic guaranteed option hedge system. *Sustainability*, 11(15), 4100.

Vila Biglieri, J.E., Małecka, J. (2019). Learning by Doing Nasdaq Face Book Experience – Case Study of Facebook Strangles. Krakow. *Horizons of Politics*, 10, 31, 81-101.

Yuandong, T., Ma, J., Gong, Q., Sengupta, S., Zhuoyuan, Ch., Pinkerton, J., Zitnick, C.L. (2019). Open Go: An analysis and open reimplementation of AlphaZero. arXiv:1902.04522. Retrieved from: https://arxiv.org/abs/1902.04522.

Yao, J., Li, Y., Tan, C.L. (2000). Option price forecasting using neural networks. *Omega*, 28, 455-466.

Yoon, Y.O., Swales, G., Margavio, T.M. (1993). A comparison of discriminant-analysis versus artificial neural networks. *Journal of the Operational Research Society*, 44(1), 51-60.

Zhang, H., Liu, F., Turner, I. (2016) Numerical solution of the time fractional Black-Scholes model governing European options. *Computer & Mathematics with Applications*, 71(9), 1772-1783.

NAJPROSTSZY MODEL ALGORYTMU GENETYCZNEGO WYCENY OPCJI – STUDIUM PRZYPADKU NASDAQ

Streszczenie

Rynek kapitałowy jest miejscem spotkania podaży i popytu. Orientacja na zysk, możliwy do osiągnięcia za pośrednictwem, giełdy stymuluje dwa procesy: 1) kupno instrumentów finansowych lub 2) ich sprzedaż, czyli długą lub krótką opcję. Inwestowanie to proces, któremu towarzyszą wahania – często na poziomie <1% dziennie. Stąd inwestorzy indywidualni poszukują rozwiązań alternatywnych, do których należą instrumenty pochodne, dziennie oscylujące nawet o 100%. Dlatego dostrzeżono potrzebę opracowania instrumentu – narzędzia wyceny – ułatwiającego inwestorom indywidualnym podejmowanie decyzji inwestycyjnych. Wykorzystywany model Blacka-Scholesa (BSM) stosuje sześć zmiennych niezależnych. Zdecydowano skompilować alternatywny model wyceny bazujący na algorytmie genetycznym (GA) na podstawie indeksów spółek notowanych na NASDAQ: Facebook, Apple, Amazon, Netflix i Google (tzw. spółki FAANG), przy zastosowaniu oprogramowania Eureqa GA. Celem artykułu jest prezentacja wyników badań będących próbą opracowania skuteczniejszego modelu wyceny opcji przez porównanie dokładności algorytmu genetycznego (GA) i Blacka-Scholesa (BSM) oraz ewaluacji luk w ruchach cen instrumentów bazowych. Komparacja algorytmu genetycznego z tradycyjnym modelem wyceny opcji Blacka-Scholesa pozwoliła na opracowanie nowego modelu inwestycyjnego o charakterze liniowym – inwestorzy mogą dokonywać prognoz za pomocą tylko jednej zmiennej – ceny akcji, co znacznie powinno zoptymalizować podejmowanie strategicznych decyzji inwestycyjnych, bowiem presja zakupowa powoduje szybki wzrost cen instrumentów bazowych, co implikuje niechęć właścicieli opcji do sprzedaży instrumentów pochodnych w momentach wzrostów ujemnych. Prezentowany model charakteryzuje większa skuteczność inwestycyjna, szczególnie istotna dla indywidualnych inwestorów, którzy zazwyczaj nie są w stanie osiągnąć efektu skali zysku na podstawie wartości detalicznego portfela inwestycyjnego.

Słowa kluczowe: NASDAQ, opcje, algorytmy genetyczne, giełda, model Blacka-Scholesa