Forecasting Prices on the Stock Exchange Using a Trading System

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Abstract. For successful trading on stock exchanges, it is important to use trading tools that will ensure success in trading operations and provide competitive advantages. The purpose of the article is to develop an algorithm for the creation of a trading system and selecting a research object whose shares may subsequently become the object of real trade. The basis of the developed trading system is the consolidated mathematical model based on several models (multipliers, neural network and discounted cash flows). The consolidated model estimates the stock price of NIKE Inc., which has a lower deviation from the actual price than the price is predicted by other mathematical models, including linear regression models, etc. The results of the work also identified directions for improving the trading algorithm: to extend the horizon of the forecast; to include TakeProfit at the predicted value; to form a stock portfolio; to cover more factors in the model.

Keywords: stock exchange, trading system, forecast, consolidated mathematical model.

1 Introduction

Nowadays forecasting is being considered as one of the most important branches of research in the economic and business fields and has been developing rapidly. Forecasting stock exchange prices by considering its dynamic factors is an important part of a business investment plan. The confidence of investors in these markets has declined and many negative problems in the world economy are present. This clearly shows the strong relationship between uncertainty in financial markets and investor confidence. Financial asset prices are influenced by numerous factors including people behavior, political, economic, competition or other factors, so price forecasting can be a difficult process.

Due to the development of stock trading, opportunities to receive a stock investment return exist. However, this is possible only with a properly selected trading strategy and efficient trading system. Many traders diversify risks and increase profits using several types of trading systems, which number more than a thousand today. However, every trader or investor is trying to develop a unique trading system which will allow anybody to successfully invest money by trading stocks with a correct price forecast.

Forecasting prices allows not only individual financial asset price information to be considered, but also financial and economic systems, and financial crises to be assessed as to their possible scale in order to make appropriate economic decisions. At the same time, the lack of a unified theory that would explain price fluctuations in stock markets and a unified methodology for predicting prices for them determines the expediency and necessity of further development of the methodology of forecasting prices on stock exchanges.

The purpose of the article is to develop an algorithm for the creation of a trading system and selection of a research object whose shares may subsequently become the object of real trade. The paper is organized as follows. The next section explores the theoretical background of forecasting prices in stock exchange. The third part describes the methodology of the research. The forth part is divided into three subsections. The first part analyzes the financial performance of the NIKE corporation and shows correlations between the economic and financial indicators of this corporation. The second part gives an assessment of the effectiveness of the developed forecasting model. In the third part the forecast of stock prices is made with the help of the developed model.

The study has several limitations. First is the time period for forecasting. Secondly, the testing was carried out using the shares of one corporation, not a portfolio, as an example. Thirdly, the TakeProfit was not included at the predicted value.

2 Theoretical Background

Forecasting prices in stock markets is a matter of great interest both in the academic field and in business. The forecasting of stock prices and stock returns is possible using various techniques and methods. Many researchers study price trends in stock markets with the help of artificial neural networks [1-2] or fuzzy-trends [3, 4]. The application of artificial neural networks has become the most popular machine learning method, and it has been proven that such an approach can outperform most conventional methods. The most popular neural network algorithm for financial forecasting is the back-propagation algorithm. However, many articles have shown that the artificial neural networks model, based on the back-propagation algorithm, has some limitations in forecasting, and it can easily converge to the local minimum because of the noise and complex dimensionality of the stock market data.

Many researchers use time-series models or other types of regressions [5-7]. Stock market time series forecasting is an interesting and open research area. Artificial intelligence algorithms are now mostly used to forecast time series. However, a highly efficient stock exchange prediction model has not been designed yet.

Hybrid models have become more and more popular recently [8-9]. Kannan, Sekar, Sathik and P. Arumugam in [10] used data mining technology to discover the hidden patterns from the historic data that have probable predictive capability in their investment decisions. Usually, the rise or fall in an international stock market is caused by some external factors. This means that stock exchange forecasting depends upon local factors and international stock exchange markets. The robustness of forecasting models remains an open research area that creates many approaches to design trade systems for stock markets.

The trading system is based on a clear algorithm or, in other words, a clear set of rules for generating trade signals (that is, the conditions for opening or closing a position). The main difference between one trading system and another is its author's approach to the rules of trading signal generation [11]. Trading systems are based on one or a limited number of algorithms. Fundamental and technical analyses are used the most often in trading systems [12-15]. Also, genetic algorithms [16] and neural networks and neuro-fuzzy computing [17] have become popular too. However, as Kaufman mentioned, "most modeling methods are modifying cations of developments in econometrics and basic probability and statistical theory. They are precise because they are based entirely on numerical data; however, they need trading rules to make them operational. The proper assessment of the price trend is critical to most trading systems" [18, p. 6]. A trading system, in the process of its operation, requires constant debugging and analysis of completed transactions within a specified interval, changing parameters for the following operations in order to maximally optimize the intended trading strategy. Therefore, forecasting prices on the stock exchange with the help of trading system of a trader will be a wide area for future research for a long time.

3 Methodology

All trading systems operate according to their logic, that is, an algorithm that reports to the system how to behave in different situations. The algorithms of trading systems are developed based on the data obtained about events that previously occurred on the stock market. The algorithm of creating a trading system includes the following stages.

The first stage in the construction of a trading algorithm is the definition of a strategy that will achieve a desired goal. The rules that formulate the strategy should be set out consistently. The main rules are the rules surrounding entering and exiting markets, that is, the terms of purchase and sale of stock commodities. Typically, a trading strategy involves risk management by limiting the amount of risk capital. A typical approach is to install a stop loss order that limits the maximum damage that is allowed under the agreement. A trading strategy can also include revenue management that protects the untapped profits generated during a lifetime position. A typical approach to managing long-run profits is to establish a retractable stop-loss for a fixed dollar value relative to the maximum of non-actualized profits. The purpose of our strategy is to verify the correctness of the forecast of prices, and not real bargains, so the stop-loss order was not used in our algorithm.

The best solution for the stock market is a strategy based on fundamental analysis, which involves an analysis of the work of business entities, as well as external market conditions. Two traditional forecasting models were used: Multiplier (M) and Discounted Cash Flow (DCF). These are classic models that do not require complex calculations or a large number of steps to calculate, although automation of calculations of these models will save several days. Since it is impossible to fully evaluate the effectiveness of stages such as testing or optimization, another model for forecasting stock market prices, the mechanical neural network (NN), which is based on economic indicators of the enterprise, was used. Thus, our consolidated model for predicting stock market prices (W) includes three models: multiplier, discounted cash flows and a mechanical neural network. For comparison, the traditional linear regression model (LM) is used (Fig. 1).

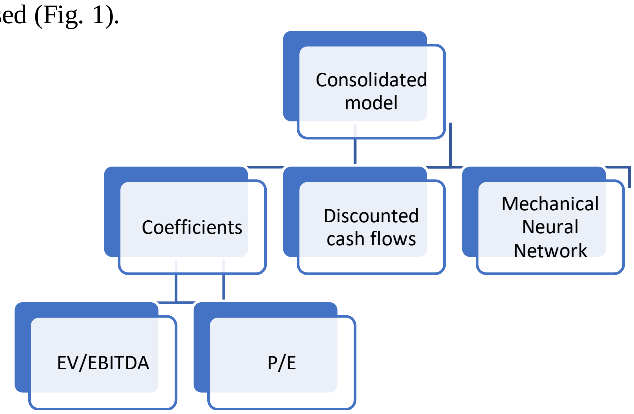

Fig. 1. Constituent methods of forecasting in the consolidated model

The second stage is to write an algorithm of action in the trading system in the programming language R, using C ++ to extract data, to automate all processes and calculations.

The third step in constructing the algorithm is testing the trading system. The testing stage has two goals: the first one is to determine if the system performs the specified functions; the second one is to check the possibility of obtaining profits and the risk of losses. The model should be moderately profitable with different price trends and over several different time periods. Not necessarily every test should show profit, but if each test is going to cause loss, then this system should be discarded.

Testing in various sectors of the economy has been used, which is necessary for the possibility of wider uses of the algorithm. For testing, the sample was limited to 10% of quarters, and at some periods of time it allows a better comparison of their reliability. Periods were chosen randomly, by the algorithm, but in a way that the trend of stock quotes and indices was versatile (downward, growing, lateral). This is necessary for a better understanding of the efficiency of the algorithm in all types of market.

In the process of testing, an important step is to check the stability of the trading system. A robust trading system will provide profits across a wide range of variables, market segments, and market conditions. In other words, a sustainable model will continue to show profitable results and in changing market conditions, which is an extremely important result of trade. Thus, testing consists of two parts:

1) Selective manual check of various computer calculations of rules and formulas.

2) Investigation of the tested transactions and checking them for deviation from the theory.

The first trading system test is the calculation of profit and loss on a segment of price history of significant duration, for example, on an annual basis. This first test gives a preliminary idea of profit and risk. The main rule is to proceed from the expectations of annual profits at the level necessary for trading in this market.

The fourth stage of work is the choice of the subject of testing and the definition of the study period. The best market for research is the US stock market, as it is liquid and has a long history that is needed for analysis. The main criterion for selecting companies is the availability of electronic reporting and more than 20 years of quotations on the stock exchange. Seven companies were selected by sectors of the economy and their financial performance for 95 quarters (30.11.1994 - 30.08.2018) was analyzed. These are the following companies:

1) AT&T Inc. (technology);
2) WALMART Inc. (wholesale and retail trade);
3) ECOLAB Inc. (means for water, hygiene, health, etc.)
4) BIOGEN Inc. (health care)
5) WELLS FARGO & COMPANY (finance)
6) NIKE Inc. (consumer goods)
7) CATERPILLAR Inc. (production goods).

To demonstrate the results of the analysis, NIKE Inc. was selected. The company's revenue structure is simple in scope, but difficult in geography, that is, its financial performance is influenced not only by the situation in the US but also in the world.

The fifth stage is the optimization of the trading system, which is carried out on the same principles as testing, but the main task is to make the use of the trading system most effective. In a practical sense, optimization is a process of calculating the indicators of many different tests of this trading system on the same segment of price data. According to certain criteria, the best test results, which provide maximum profit potential in real trade, are selected, and they will be the basis for the optimization of the trading system. The object of optimization is the coefficient of reliability of the model, with which it is possible to achieve the best consolidated forecast.

The optimization has five components: (1) selection of model parameters; (2) setting the ranges of their scanning; (3) determination of the sample size; (4) determination of criteria for evaluation, selection of a better model; (5) determine the criteria for evaluating the test forecast as a whole. In the process of optimization, we should use the model parameters that have the most impact on its effectiveness. If the parameter has a small effect on efficiency, there are no reasons to make it a candidate for optimization. Instead, it should be assigned a fixed value (constant) for optimization time.

If optimization shows improved results, it is time to move to the final step of the testing process, namely, forward analysis. Forward analysis evaluates the effectiveness of the trading system solely on the basis of post-optimization trading or test data that are not part of the optimization sample. This level of testing answers two of the most important questions about our trading system: 1) the correctness of the forecast of prices 2) the possibility of profit after optimization.

The sixth stage is an assessment of the ratio of real trade indicators with projected indicators. If the real figures differ much from the test ones for no clear reasons, then a need to return to step number three is warranted.

The mathematical formalization of the processes embedded in the trading system algorithm and designations used in the study are as follows:

1. On the basis of the current financial report, forecasts are made for three models (NN, DCF, M)
2. The consolidated forecast price is based on formula (1):

$$Pr\_Price = Knn * Pr\_NN + Kdcf * Pr\_DCF + Km * Pr\_M, \qquad (1)$$

Pr_Price is the consolidated forecasted price,
K - coefficient of reliability of the model,
Pr_ - forecasted price by model
NN - model of mechanical neural network,
DCF - Discounted Cash Flow Model
M - model of multipliers.

3. Determination of projected income by formula 2:

$$Pr\_Prof = | Pr\_Price - Now\_Price | / Now\_Price, \qquad (2)$$

Pr_Prof is a projected income,
Pr_Price is the consolidated forecasted price,
Now_Price is the actual current price.

4. The decision to enter the market based on the assessment of the appropriateness of investment, which is calculated by the formula 3:

$$Pr\_Prof - Km\text{-}Slip > RF\_Rate / 4, \qquad (3)$$

Km - commission for the opening and closing of a position,
RF_Rate - without a risky interest rate
Slip - slippage
RF_Rate is a risk-free investment rate.

5. Closing a position on the day on which the forecast was made.

The concept of exit from the market implies the absence of StopLoss and TakeProfit, since the receipt of real profit is not the main goal, but only one of the indicators for checking the efficiency of the trading system. The main goal is to determine the price trend and price value for the planned closing date of the position.

Next, it is necessary to detail the information on one of the models, namely the model of the mechanical neural network, which entered the consolidated model and contains the largest number of economic indicators. Indicators that will be analyzed in the neural network were selected based on the main indicators of financial reporting, namely:

From the report on financial results:

1) Rev (Revenue) - Revenue;

2) Inc (Net Income) - net profit;

3) Div (Dividends declared per share (in dollars per share)) - dividends on ordinary shares (in dollars per share).

From the balance:

1) Ast (Total assets) - aggregate assets;

2) Ldbt (Long-term debt) - long-term liabilities;

3) Sheq (Total shareholders' equity) - share capital;

4) Curl (Total current liabilities) - current liabilities.

From the Cash Flow Statement

1) Cash_op (Cash provided by operations) - cash flow from operating activities;

2) Cash_inv (Cash used by investing activities) - cash used in investment activities;

3) Cash_fin (Cash used by financing activities) - cash flow used in financial activities.

Additional indicators were also used such as:

1) Price_1 is a stock price at the time of the report's release;

2) S & P 500 is the stock index in which Nike is located;

3) Qw_1 / 2/3/4 - quarters of the marketing year of Nike;

4) Price_2 is a stock price for three days before payment of dividends for the forecasted quarter.

Additional indicators are needed to better understand the environment:

"Price_1" is required for the neural network to be able to track the price change and understand what indicators have influenced it more,

"The S & P 500 Index" is needed to understand the situation in the economy and the US stock market.

Quarters as indicators needed to understand the cyclicity algorithm present in this market, as established by research. The above indicators are independent variables, the only dependent variable in this model will be Price_2.

4 Efficiency Estimation Procedure

4.1 NIKE Inc. Financial and Economic Indicators Analysis

According to the New York Stock Exchange (NYSE), the shares of the company grew more than 33 times (Figure 2) over the past twenty-four years, that is, the rate of growth - an average of 16% annually. However, the highest growth rates have been since 2009, when the company's products have gained popularity and spread around the world.

Fig 2. The price dynamics of NIKE Inc., 11.1994 - 03.2018, USD. US / share (Source:: NYSE)

Interaction of Financial Results Indicators with NIKE Inc. depicted in Fig. 3.

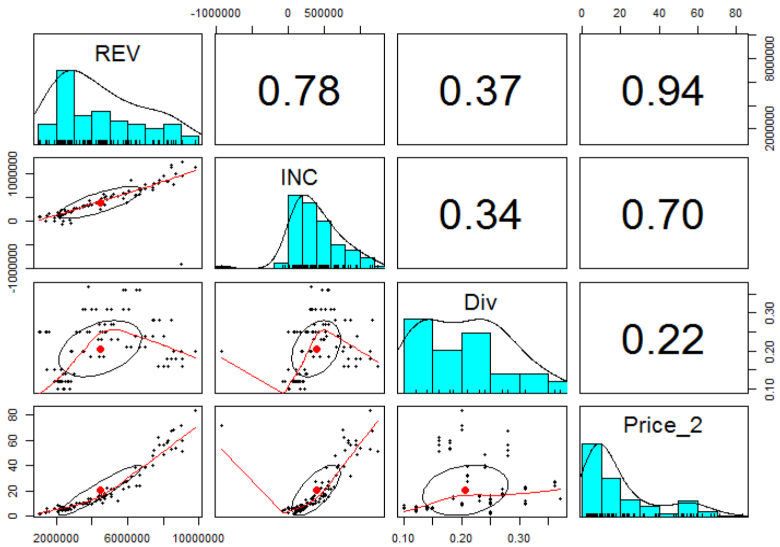

Fig. 3. Correlation coefficients, scatter plot, and distribution histogram between revenue, profit, dividends and share price of NIKE Inc.

Explanations to the figure 3:

Revenue	Coefficient of correlation between revenue and profit	Correlation coefficient between revenue and dividends	Coefficient of correlation between revenue and price
Scatter plot between revenue and profit	Profit	Coefficient of correlation between profit and dividends	Coefficient of correlation between profit and price
Scatter plot between earnings and dividends	Scatter plot between profits and dividends	Dividends	Correlation coefficient between dividends and price
Scatter plot between revenue and price	Scatter plot between profit and price	Scatter plot between dividends and price	Price

As can be seen from the scatter plot, the revenues are positively interdependent with net profit and stock price, with the profit being a linear dependence of disproportionate growth. On the contrary, with the price of the stock, the interdependence is nonlinear, and the more accelerated rate of growth of prices from the growth of revenue. The net profit also correlates positively with the company's price, this dependence is also nonlinear and has hyperbolic acceleration function.

The Pearson correlation coefficients show that the largest share price correlates with income (0.94), less correlated with net profit (0.7) and has a slight correlation with dividends. In general, dividends moderately correlate with all indicators and are placed on the chart rather chaotic.

A distribution histogram is located on the central diagonal. Here it is necessary to note the full asymmetry on the right side (net profit and share price of the company) due to the long-term presence of the company in the medium-sized business, dividends and earnings are asymmetrical to the right, but they are more evenly arranged.

Next to be considered is how interrelated indicators balance with the predicted price in Figure 4. The aggregate assets have a strong proportional relationship with all the analyzed indicators; this is evident in the plot of scattering of the sample elements, as well as by the coefficient of correlation, which is higher than 0.8. Scattering in almost all cases is based on a linear function. There is a very interesting scatter plot between long-term capital and equity capital; initially the values take hyperbolic acceleration, then after 70% of the sample changes to the function of the hyperbolic cosine region, that is, the inverse hyperbola, which in our opinion is associated with an increase in the interest rate by the Fed of 2%. This influenced the decision on how to raise funds for financing the range; the absence of less costly loans prompted investors to find investors in the stock market.

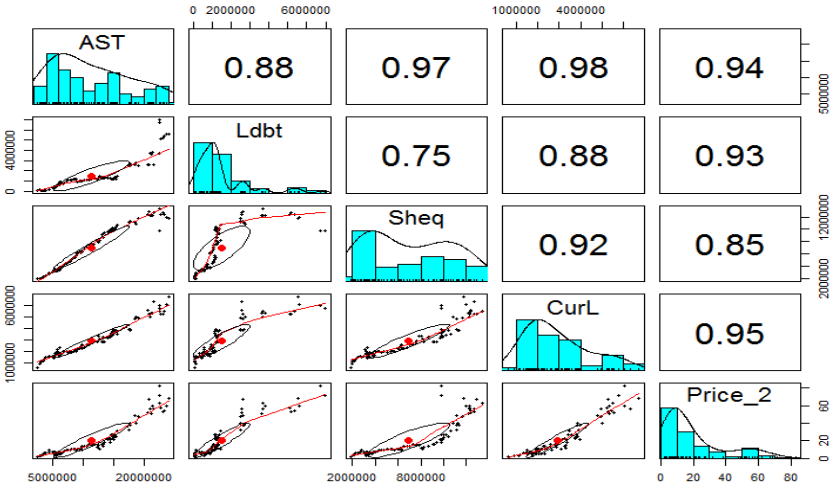

Fig. 4. Correlation coefficients, scatter plot and histogram of distribution between assets, share capital, liabilities and share price of NIKE Inc.

Explanations to the figure 4:

Assets	Coefficient of correlation between assets and long-term liabilities	Coefficient of correlation between assets and equity	Correlation coefficient between assets and current liabilities	Coefficient of correlation between assets and price
Scatter plot between assets and long-term liabilities	Long-term liabilities	Coefficient of correlation between long-term liabilities and share capital	Coefficient of correlation between long-term liabilities and current liabilities	Coefficient of correlation between long-term obligations and price
Scattering Scale between Assets and Equity	Scatter plot between long-term liabilities and share capital	Equity	Correlation coefficient between share capital and current liabilities	Correlation coefficient between share capital and price
Scatter plot between assets and current liabilities	Scatter plot between long-term liabilities and current liabilities	Scatter plot between current liabilities and current liabilities	Current liabilities	Coefficient of correlation between current liabilities and price
Scatter plot between assets and price	Scatter plot between long-term obligations and price	Scatter plot between current liabilities and price	Scatter plot between current liabilities and price	Price

As in the figures in Figure 3, distribution histograms have right-side asymmetry (Figure 4), which indicate that the company is growing.

Spearman's correlation calculations (Figure 5) showed a close correlation between the price of a company's shares and independent variables, in particular the S & P 500 market index. This suggests that external factors are also influenced by the price of NIKE shares.

	REV	INC	Div	AST	Ldbt	Sheq	CurL	Price_1	S.P.500	Cash_op	Cash_inv	Cash_fin	Price_2
REV	1.00	0.90	0.46	0.98	0.96	0.97	0.97	0.96	0.74	0.32	0.01	-0.38	0.95
INC	0.90	1.00	0.50	0.89	0.85	0.90	0.87	0.88	0.67	0.26	-0.06	-0.30	0.88
Div	0.46	0.50	1.00	0.47	0.43	0.50	0.46	0.45	0.13	0.22	0.01	-0.27	0.47
AST	0.98	0.89	0.47	1.00	0.97	0.98	0.98	0.96	0.76	0.38	-0.02	-0.40	0.95
Ldbt	0.96	0.85	0.43	0.97	1.00	0.95	0.94	0.93	0.73	0.40	-0.07	-0.40	0.92
Sheq	0.97	0.90	0.50	0.98	0.95	1.00	0.95	0.95	0.72	0.40	-0.06	-0.42	0.95
CurL	0.97	0.87	0.46	0.98	0.94	0.95	1.00	0.93	0.78	0.32	0.00	-0.35	0.93
Price_1	0.96	0.88	0.45	0.96	0.93	0.95	0.93	1.00	0.73	0.37	-0.04	-0.39	0.98
S.P.500	0.74	0.67	0.13	0.76	0.73	0.72	0.78	0.73	1.00	0.32	0.02	-0.30	0.71
Cash_op	0.32	0.26	0.22	0.38	0.40	0.40	0.32	0.37	0.32	1.00	-0.25	-0.78	0.38
Cash_inv	0.01	-0.06	0.01	-0.02	-0.07	-0.06	0.00	-0.04	0.02	-0.25	1.00	-0.01	0.00
Cash_fin	-0.38	-0.30	-0.27	-0.40	-0.40	-0.42	-0.35	-0.39	-0.30	-0.78	-0.01	1.00	-0.40
Price_2	0.95	0.88	0.47	0.95	0.92	0.95	0.93	0.98	0.71	0.38	0.00	-0.40	1.00

Fig. 5. Spearman correlation coefficient between the investigated parameters

4.2 Estimation of Efficiency of the Developed Model of the Forecast of Prices

One of the objectives of the study is to evaluate the effectiveness of the model, and one of the best methods of evaluation is a comparison with the traditional model. The classic method of forecasting, which is widely used in many spheres, is linear regression. Therefore, a regression model of stock price forecast was constructed.

Further work was aimed at constructing, testing, optimizing, testing the reliability of the consolidated model, which included several models: neural, multiplicative and discounted cash flows with the help of computer equipment. In Table 1, projected prices for different models and the actual price at the end of the projection period can be compared. The date of forecasting is chosen independently by the program.

The final step in optimization is to determine the weight of each model in the consolidated forecast model, that is, at the forecasted price. The values of the mean-square deviation are as follows: for the neural network - 0,778; for multipliers - 0.134; for discounted cash flows - 0.088. This indicates the greatest impact of the neural model on the consolidated weighted price. This model, after optimization, gave the most accurate forecast.

Table 1. Actual and forecasted stock price figures for NIKE Inc. during test periods, US $ / share

Data	Pr_P_NN	Pr_P_M	Pr_P_DCF	PR_P_LM	Pr_Price	Now_Price
31.05.2001	5,175	5,358	6,403	4,553	5,307	6,313
31.05.2002	6,186	6,555	8,241	6,036	6,416	5,719
28.02.2003	7,180	5,679	6,548	6,051	6,923	6,498
31.05.2007	13,366	12,797	14,820	11,208	13,417	13,53
30.11.2007	15,731	14,777	18,244	17,081	15,824	15,175
29.02.2008	16,753	13,561	15,816	15,965	16,243	16,23
30.11.2009	15,830	14,847	16,230	15,729	15,733	16,143
30.11.2010	20,236	21,092	21,269	21,346	20,442	22,073
30.11.2015	63,028	66,428	66,328	67,843	63,774	62,46

Figure 6 illustrates the deviation of the consolidated forecast price (Pr_Price) and the price calculated by the linear model (Pr_P_ LM) from the actual price (Now_Price). As can be seen from Figure 6 and Table 1, the forecasted prices for the model we have developed are deviating less from the actual price line than the forecasted prices constructed according to the linear model, which indicates the undeniable advantages of the first model.

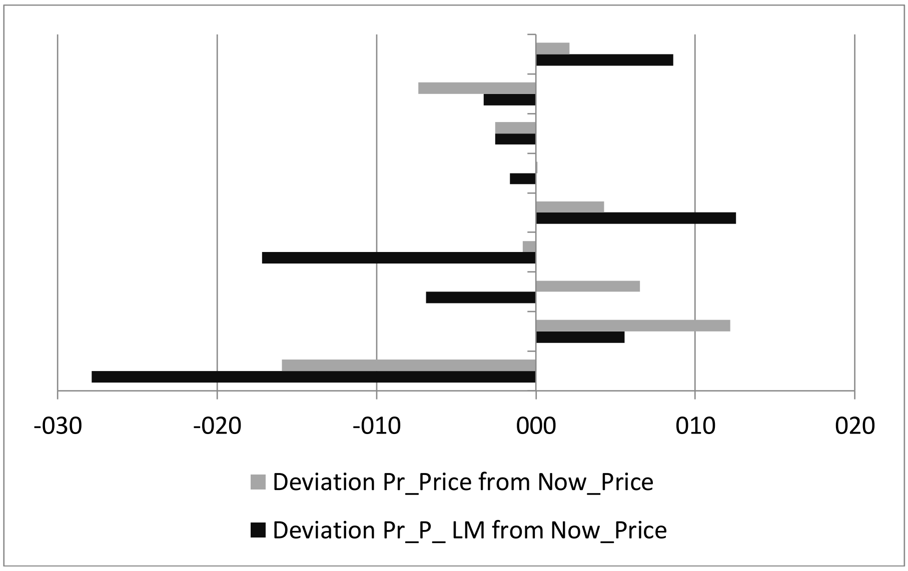

Fig. 6. Comparison of forecasted prices based on the consolidated model and the linear model with respect to actual prices for shares of NIKE Inc.,%.

A trading system based on a weighted model correctly identified the direction of price movement in 44% of cases, while 22% of trade signals differed from real price dynamics directly opposite, and 34% of trading signals differed slightly from the real price movement. It should also be noted that 66% of the predicted values indicated the presence of a bear market, while the actual values in only 33% of observations in the next period showed a falling trend.

For comparison, the trading system based on a linear model correctly predicted the direction of prices only in 33% of the cases, another 33% of trading signals differed directly opposite from the real price dynamics, and the remaining 34% had a slight deviation from the real movement of prices. In one case, the trading system recommended not entering the market while during this period there was a bullish trend, so earnings opportunities would have been lost, and in two cases the system recommended taking a short position, when in fact the market during the quarter was in a side movement.

4.3 Forecast of Prices Using the Developed Trading Model

Since the testing did not give a precise assurance of the efficiency of the model, a forward test had to be carried out, that is, an analysis of the forecasted price within the actual time period that was not investigated nor considered. This is best done on the broker's demo account using the whole sample of data (95 quarters) to predict, not the 10% as used during testing.

For the forecast, a period was chosen that was not used in the model (31.08.2018-30.11.2018) and a quarterly forecast of stock prices of NIKE Inc. was made. (Figure 7, Table 2).

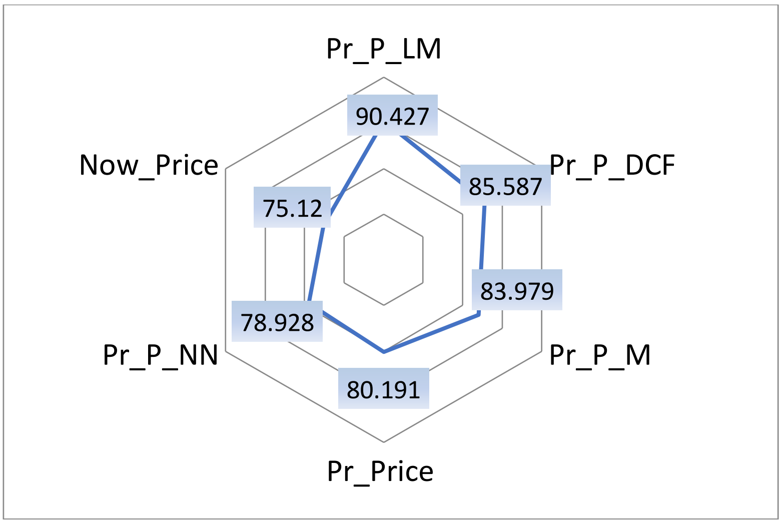

Fig. 7. Estimated price models and actual share price for NIKE Inc. as of 30.11.2018, USD US / share

Table 2. Comparison of NIKE Inc.'s forecasted price models and actual prices. as of 30.11.2018, USD US / share

Designation of models	Actual price (Now_price) (as of 31.08.2018	Estimated price as of 30.11.2018	Actual price (Now_price) as of 30.11.2018	Rejection of projected prices from actual
Pr_P_DCF	82,20	85,59	75,12	10,47
Pr_P_M	82,20	83,98	75,12	8,86
Pr_P_NN	82,20	78,93	75,12	3,81
Pr_Price	82,20	80,19	75,12	5,07
Pr_P_LM	82,20	90,43	75,12	15,31

Thus, the biggest difference between the forecast and actual price as calculated based on linear regression model was $15.31 per share. The smallest deviation from the projected price from the actual demonstration was the model based on the neural network at $3.81 per share. This model has the greatest impact on the consolidated weighted price, so the deviation from the actual price was $5.07 per share.

Both the neural network model and the consolidated model predicted lower prices at the end of the examined quarters than at the beginning. However, all other models predicted a bullish trend, which proved to be false. The joint impact of model multipliers (M) and the discounted cash flow model (DCF) had a negligible effect on the consolidated model.

During the period in which the forward analysis was conducted there were no significant changes in the company's policy nor strategy, and the projected figures for the following year were not revised. However, there was a negative marketing impact when the company's major advertising face, Cristiano Ronaldo, was accused of personal income tax evasion. This news alone could have provoked a downward trend in prices that we could predict using a trading system based on our consolidated model, which showed better results than the linear regression model, and the two models, neural network and discounted cash flows, which had been tested separately

5 Conclusions

Consequently, the created trading algorithm is capable of allowing predictions to be made of the company's share price with a fairly high accuracy using the consolidated model. The largest influence on the company's share price is made by indicators such as revenue, net profit and aggregate assets for which the correlation coefficient is more than 0.95. The company has a sound dividend policy, so dividend changes have little effect on price dynamics.

The results of the work also identified directions for improving the trading algorithm.

1) In further research, we plan to extend the horizon of the forecast, as the stock market is one of the best environments for long-term investment. It will also simplify the calculations, namely, deviating from the analysis of quarterly indicators to annual.

2) In many cases, test tests, if we put TakeProfit at the predicted value, we could profit before, and sometimes even avoid losses. Therefore, in the future, we plan on using two models to determine the expediency of buying shares, and the neural network to determine when it is best to buy or sell shares.

3) In order to diversify risks, it is expedient to use not only shares of one company for forecasting but also to form a stock portfolio for investing funds.

4) The broader coverage of the fundamental factors that will be included in the model for analysis will only improve the results of the work.

Improving the trading system will allow more accurate forecasts and, accordingly, more effective investments in the stock market.

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