FEATURES OF FORECASTING STOCK PRICE CHANGES OF OIL PRODUCTION COMPANIES USING COMBINATIONS OF TREND AND NON-TREND INDICATORS

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Abstract*. Today, a company's share price is influenced by a wide array of factors, ranging from fundamental internal dynamics to political decisions, industry-specific developments, macroeconomic conditions, and global trends. Investors face challenges in selecting an appropriate approach to identifying the target industry and asset, interpreting analysis results, and determining the optimal market entry point. In this context, several pertinent issues emerge regarding forecasting share price changes for oil production companies (BP p.l.c, Chevron p.l.c, Exxon Mobil Corp., Shell p.l.c) on the stock exchange, particularly concerning the use of technical analysis tools like moving averages and oscillators. This study examines the impact of different moving average settings and their combinations on the accuracy of predicting share price movements. Based on these findings, tasks addressed by such indicators are identified, and a systematic approach to selecting technical analysis tools and their configurations is proposed. The paper explores various methods for forming and interpreting signals generated by individual indicators and their combinations, focusing on their implications for forecasting asset price changes. Several criteria are proposed for evaluating the effectiveness of these approaches during the testing phase. The study compares and analyzes the results of multiple forecasting system configurations, identifying the optimal ones according to the selected criteria. Calculations are based on weekly stock data spanning 2000 to 2024, from which the most effective combination of indicators for the forecasting system is determined. Potential areas for optimization and additional tools to enhance the system are also outlined. Finally, the study concludes that the proposed approach to constructing a forecasting system is viable for executing real stock transactions with the selected companies' shares.*

Keywords*: quotes; technical indicator; moving average; simple moving average; exponential moving average; linear weighted moving average; oscillator; stock exchange; stock exchange operation; stock market.*

JEL Classification**: *G10, G17; G 32***

Formulas*: 4;* ***fig****.:0;* ***tabl****.:8;* ***bibl****.:25*

Introduction. Today, the oil extraction and refining industries are pivotal for nations and the global economy due to their geopolitical influence, energy security, strategic importance, impact on labor markets, infrastructure development, related industries, tax contributions, and overall contribution to a country's GDP. Consequently, these industries attract significant interest from investors, governments, and businesses alike.

Understanding the trends in the stock prices of companies within this sector is crucial for economic agents involved in resource allocation within the national economy. For businesses, this knowledge informs decisions on financing options, dividend payments, and more. For investors, it provides insights into market expectations regarding a company's prospects, serving as a foundation for decisions on investing in or divesting from company assets. For governments, it offers a perspective on the industry's and individual companies' outlooks for the upcoming fiscal period, as representatives of such a vital sector may require support during periods of economic turbulence.

The stock market is a system in which numerous participants interact, and through this interaction, expectations regarding the true and fair value of assets listed on relevant stock exchanges or traded on over-the-counter markets are formed (Cullen, 2024). These expectations, their fluctuations, and the actions of participants driven by these expectations significantly influence market prices. In turn, market prices also have a substantial impact on participants' expectations (Soros & Volcker, 2003).

Thus, analyzing changes in a company's asset prices can provide stakeholders with valuable information necessary for making informed economic decisions. It is also worth noting that the lack of awareness among a broad range of retail and some institutional investors about certain aspects of asset price dynamics analysis creates opportunities for unscrupulous companies. These entities often exploit prevailing market sentiments, leading to capital losses for investors who engage with them (Bobrov, 2013).

As part of our study, we will examine technical indicators as a tool that can be used for forecasting changes in a company's asset prices.

Literature review. The use of technical analysis indicators for forecasting stock prices on the stock market has been extensively covered by the academic community. However, the specific features of forecasting stock price changes in the oil extraction and refining industries using these tools have not received sufficient attention. We see an opportunity to explore and highlight this issue further.

In general, some researchers approach the analysis of technical indicators in a standardized way, assuming that these tools are equally applicable and effective across all instruments. Additionally, the timeframes used to build forecasting models often exclude periods of market turbulence, which, in our opinion, calls into question the effectiveness of the developed systems.

Another group of researchers extensively employs machine learning methods, focusing primarily on selecting the appropriate algorithm for the task. In such studies, the final set of indicators or parameters used by the software to generate recommendations is often not disclosed. As noted by Zhao et al. (2023), this approach loses the context of the intrinsic value of assets and market sentiment regarding specific asset prices.

In our view, such an approach shifts the problem from the domain of economics, where the allocation of limited resources under conditions of unlimited needs is addressed, to the realm of computer science.

Thus, among recent studies focusing on optimizing investment decision-making, risk allocation, and resource management using technical analysis indicators, we can highlight several notable contributions. Fazeli and Houghten (2019) analyze the potential of machine learning with three classical indicators, using standard settings to predict stock prices for four companies listed on the NYSE. Notably, the data analyzed covers a period of only five years: 13.03.2014 – 12.03.2019.

Chen, Gong, and Ming-Tai Wu (2021), in their study, employ a wide range of technical indicators to train machine learning algorithms, which are then used to construct a model for forecasting asset prices (specifically, the stocks of leading technology companies listed on the NYSE and TWSE). However, the results do not specify which combinations of indicators or settings were selected by the final algorithm, and the testing period only covers 2018–2019. It is also noteworthy that the researchers highlight differences in investor behavior regressors between the U.S. and Taiwanese markets: on the NYSE, options significantly influence asset prices, whereas futures play a more prominent role on the TWSE.

Dhafer et al. (2022), in their study, combine technical indicators with standard settings in various combinations to train a neural network to forecast price changes for a single asset listed on the KLSE. The data used for calculations covers the period from 2008 to 2017.

Bang and Ryu (2023) utilize the visualization of certain technical indicators to train a machine learning algorithm for identifying graphical patterns that form on price charts. The modeling is based on stock price data of NASDAQ100 index companies from 2000 to 2022. However, the authors do not specify the final indicator settings that yielded the best results for the model.

Hani'ah et al. (2023) analyze the effectiveness of a neural network that combines moving averages with search trend data. The researchers utilize stock price data from the KLSE for the period 2017–2022. However, the resulting indicator settings are not disclosed, and the model's testing was conducted over a period of only one month.

Zhang & Tang (2023) employ momentum, trend, and volume indicators in their research to compare their effectiveness against other methods of forecasting asset prices related to emissions quotas.

Fu & Zhang (2024) propose a stock price forecasting model that combines a series of technical indicators with standard settings and a market sentiment extraction model based on textual data. Notably, the model is applied to only two assets and within a limited timeframe of 2020-2022.

Saud & Shakya (2024) analyze the optimization of a forecasting system based on trend indicators and oscillators by filtering out false signals. The study uses randomly selected companies listed on NEPSE, BSE, and NYSE. However, the researchers do not disclose the final settings of the indicators or their combination that yielded the reported results.

Wang, Hsiao & Liou (2024) examine the use of combinations of trend and non-trend indicators in conjunction with news analysis to optimize the accuracy of asset price forecasting on the TWSE. The model is built and tested using data only from 2016-2017.

To address this research gap, this paper investigates the predictive significance of chosen indicators, their settings and combinations and evaluates their effectiveness in delivering accurate forecasts.

Aims. The aim of the study is to compare the effectiveness of using trend-based, non-trend-based technical indicators, and their combinations in forecasting changes in the stock prices of oil companies, with the goal of maximizing resource allocation efficiency by economic agents.

Methods. This paper is based on the traditional methods of scientific knowledge: analysis and synthesis – in developing the forecasting system in the context of optimal resource allocation; comparison and compilation – to compare the received results with a benchmark approach; statistical method – tracking the performance of the developed systems; scientific support methods – to summarize and to formulate conclusions on forecasting system development approach. These methods allow to identify the challenges and opportunities for economic agents to develop a stock price change forecasting system to achieve the goals of efficient resource allocation.

Results. Consequently, the quotations of four international companies holding leading positions in their respective industries and whose shares are publicly traded and listed on liquid exchanges (NYSE, LSE) were analyzed. The data is presented in Table 1.

Table 1. Data on current market capitalization and revenue for companies, as reported in the last four quarters

Rank by revenue	Назва компанії	Виручка, $ млрд.	Market cap, $ млрд.	Біржа
4	Exxon Mobile Corp.	339,87	517,17	NYSE
5	Shell p.l.c.	296,76	199,44	LSE
7	BP p.l.c.	195,57	77,73	NYSE
8	Chevron Corp.	194,01	288,69	NYSE

Source: compilled by authors based on: *Nasdaq (n/d), London Stock Exchange (n/d), CompaniesMarketCap (n/d)*

Within the framework of this study, quotations were interpreted using technical analysis indicators. A technical analysis indicator is a tool for mathematically transforming information about an asset's price over a specific time period. In other words, indicators are a tool for transforming information, including expectations of market participants regarding the price of a particular asset. Based on their functional features, indicators are divided into volatility (non-trend) and trend indicators. The moving average (MA) is a trend indicator, while oscillators are, respectively, non-trend indicators. Moving averages, by smoothing the price over a specified period in the settings, filter out sharp price movements and help the analyst determine the direction of the trend. In turn, oscillators help to identify potential overbought or oversold areas of the asset and indicate possible turning points (Chart School, n/d).

Approaches to building indicators and conducting simulations used in the study. To test a trading strategy built using technical indicators, it is necessary to consider that:

1) all buy and sell signals must be binary to exclude human interpretation errors;
2) the strategy must generate a result that exceeds the potential result from buying and holding (Buy and Hold strategy) of the corresponding asset over the modeling period;
3) the modeling should cover different time periods (Aronson, 2011).

The order of our calculations was as follows:

1) data for calculations, construction, and testing of the system for each asset was divided in a ratio of 80% for system construction (system construction period in Table 2) and 20% for its verification (system verification period in Table 2), as is customary when analyzing time series data (Joseph, Vakayil, 2021). Calculations were performed in MS Office Excel;

Table 2. Information on assets selected for modeling

№	Company	Ticker	System development period	System verification period
1	BP p.l.c.	BP	2002—2017 pp.	2018—2024 pp.
2	Chevron Corp.	CVX	2000—2017 pp.	2018—2024 pp.
3	Shell p.l.c.	SHEL	2005—2020 pp.	2021—2024 pp.
4	Exxon Mobile Corp.	XOM	1999—2017 pp.	2018—2024 pp

Source: compilled by authors based on Metatrader4 software data.

2) then, simple (simple moving average – SMA), exponential (exponential moving average – EMA), and linearly weighted (linear-weighted moving average – LWMA) moving averages were calculated (Murphy. 1999). The formulas for calculation are presented in Table 3. Indicator values were calculated for periods of 2-55 (period – one week) based on opening and closing prices, and it was checked which of them best meet the defined criteria. In turn, the selection criterion was chosen as the maximum average value (Savchenko, 2023);

Table 3. Formulas for calculating

Indicator	Formula
LWMA	$LWMA_n = \sum_{i=1}^{n} P_i * W_i \Big/ \sum_{i=1}^{n} W_i$
EMA	$EMA_n = EMA_{i-1} + (2/_{n+1}) * (P_i - EMA_{i-1})$
SMA	$SMA_n = \frac{1}{n} \times \sum_{1}^{n} P_i$
Oscillator	$O = MA_a - MA_b$

Notes: n — number of periods, over which indicator is calculated, P_i — asset quote in period i (in our calculations this will be the closing price), MA_a – moving average, calculated by the appropriate method based on the asset's quote in period a (in our calculations this will be the closing or opening price), MA_b – moving average, calculated by the appropriate method based on the asset's quote in period b (in our calculations this will be the closing or opening price), W_i — weight of price and periods.
Source: compilled by authors based on: Murphy, 1999, Savchenko, Bobrov, 2024

3) subsequently, one moving average of each type that exhibited the best performance was selected, and combined systems were constructed using these averages. The effectiveness of these combined systems was then evaluated on a holdout period;

4) various oscillator configurations were calculated using the approach outlined in our previous research (Savchenko, Bobrov, 2024). Specifically, the difference between short-, medium-, and long-term moving averages was calculated to generate an oscillator. The oscillator with the highest absolute value was selected. Up to three such oscillators that met the chosen optimality criteria were selected;

5) combined systems were then constructed using the best combinations of moving averages and oscillators. The combination that demonstrated the best performance was chosen;

6) on the holdout period, trading simulations were conducted using forecasting systems based on the best combinations of moving averages, oscillators, and the combined moving averages and oscillators;

7) based on the calculated data, conclusions were drawn regarding the feasibility or infeasibility of using the approach compared to the basic "buy and hold" strategy.

Here's a breakdown of the trading signals used in the research: following the trend and crossovers for moving averages, for oscillators — following the increasing or decreasing of value. And for combined signals (MA and oscillator combinations): concordant signals – when all three moving averages indicate the same direction (up or down), the trade is executed based on that direction, discordant signals – when the moving averages provide conflicting signals, the oscillator's signal is used to determine the trade direction. Here's a breakdown of the trading actions based on the signals:

1) If the indicator (or combination of indicators) suggested that the asset's price would increase:

a) close short positions: Any existing short positions were closed at the closing price of the respective trading week;

b) open long positions: A new long position was opened at the opening price of the new trading week;

2) If the indicator (or combination of indicators) suggested that the asset's price would decrease:

a) close long positions: Any existing long positions were closed at the closing price of the respective trading week;

b) open short positions: A new short position was opened at the opening price of the new trading week.

Model Construction. Models were constructed using moving averages. The results of modeling using moving averages on the test period are presented in Table 4 below.

Table 4. Results of strategies with selected moving averages in the test period

Ticker	SMAc		SMAo		EMAc		EMAo		LWMAc		LWMAo	
	t	Result, $	t	Result, $	t	Result, $	t	Result, $	t	Result, $	t	Result, $
BP	9	567,5	3	-501,3	4	284,1	3	-672,1	12	533,6	4	-539,4
BP	18	646,8	15	566	20	358	9	297,4	14	623,9	11	227,4
BP	43	210,1	32	-879,4	28	181,5	13	465,4	27	260,6	16	386,3
BP	-	-	40	259,8	-	-	28	314	-	-	28	136,1
CVX	5	27,89	8	-129,69	4	-107,4	5	-98,15	2	25,37	4	-80,54
CVX	6	-99,49	14	-96,69	18	-78,81	14	-40,31	3	-67,69	25	-86,16
CVX	24	52,13	49	96,86	34	-68,78	28	49,33	14	19,61	27	-54,17
CVX	50	100,83	-	-	-	-	-	-	26	-50,48	-	-
CVX	-	-	-	-	-	-	-	-	41	-57,92	-	-
SHEL	10	3789	12	4213	8	3559	10	3507	2	3334,6	12	3639,84
SHEL	17	5344	19	5363	21	4785	26	3608	22	5503,04	26	4348,04
SHEL	27	3612	27	4061	27	4570	32	4256	27	5385,04	27	4472,04
XOM	7	-102,36	6	-119,45	2	-46,69	2	39,97	6	11,71	5	-117,32
XOM	18	-104,47	16	-103,75	20	-81,42	5	-70,79	11	-46,89	22	-105,6
XOM	38	-67,63	28	-59,6	38	-109,64	22	73,98	21	-101,15	27	-89,96
XOM	-	-	-	-	-	-	26	-100,44	30	-77,16	-	-
XOM	-	-	-	-	-	-	27	-98,92	-	-	-	-

Notes: *EMA* — exponential moving average, *SMA* – simple moving average, *LWMA* – linear weighted moving average, *o* – moving average is built based on opening prices, *c* – moving average is built based on closing prices, *O* – oscillator, *t* – period.
Source: compilled by authors.

Using these moving averages, strategies were further constructed using combinations of moving averages and oscillators. The best modeling results using these combinations are shown in Table 5.

Table 5. Results of the best strategies for test periods

Ticker	Indicators combination	Result, $	Forecast correctness	Mx	As	Exc	Mo	Me	Std
BP	(S9c + S18c + S43c)	411,25	51,87%	0,9609	0,1307	2,7091	6,0000	0,9000	14,8072
BP	(S7o + S15o + S40o)	341,00	51,18%	0,8081	0,1545	2,6965	5,0000	0,5000	14,9006
BP	O(E4c - E20c)	623,00	50,90%	0,7461	0,3080	2,0555	-9,0000	0,5000	14,0871
BP	O(S18c - S43c)	450,50	49,49%	0,5703	0,5323	2,2109	-3,5000	-0,0250	13,7894
BP	O(S15o - S32o)	1153,70	51,69%	1,4403	0,4911	2,0607	5,0000	0,8500	13,8640
BP	(S9c + S18c + S43c) + O(S15o - S32o)	484,30	51,83%	0,5921	0,0696	2,1641	9,0000	1,0000	14,0991
BP	(S7o + S15o + S40o) + O(S15o - S32o)	631,80	50,69%	0,7888	0,1723	2,1925	-3,5000	0,5000	13,9163
BP	(S9c + S18c + S43c) + O(S18c - S43c)	690,20	50,95%	0,8704	0,2042	2,2622	6,0000	0,5000	13,7586
CVX	(S5c + S24c + S50c)	59,83	52,93%	0,1298	1,3819	15,5143	0,0000	0,1300	2,7651
CVX	(L2c + L14c + L55c)	54,43	53,17%	0,1191	0,6030	8,0328	1,0900	0,1500	2,5631
CVX	O(S49o - S8o)	92,92	50,94%	0,1093	-0,0411	10,7361	0,9200	0,0350	2,6467
CVX	O(L4o - L25o)	95,08	51,60%	0,1088	-0,0140	10,9209	0,7300	0,0650	2,6198
CVX	O(S6c - S24c)	89,67	52,34%	0,1025	-0,8701	11,0647	0,6100	0,1000	2,6186

Ticker	Indicators combination	Result, $	Forecast correctness	Mx	As	Exc	Mo	Me	Std
CVX	(S5c + S24c + S50c) + O(L4o - L25o)	142,22	54,35%	0,1627	0,8400	10,7556	0,7300	0,2500	2,6170
CVX	(S5c + S24c + S50c) + O(S6c - S24c)	142,93	54,40%	0,1633	0,8848	10,7577	0,9200	0,2300	2,6156
CVX	(L2c + L14c + L55c) + O(S6c - S24c)	177,65	54,29%	0,2030	-0,1914	11,0862	0,0200	0,1900	2,6128
SHEL	(S12o + S19o + S27o)	4013,00	58,12%	8,0436	0,0032	2,2805	18,0000	9,0000	58,5905
SHEL	(L2c + L22c + L27c)	4258,00	56,69%	8,9086	0,0730	2,1683	2,0000	7,2500	56,0060
SHEL	O(L22c - L27c)	2002,00	52,63%	2,5697	-0,0230	2,1313	2,0000	2,5000	54,8995
SHEL	O(S17c - S27c)	3219,00	52,25%	4,1324	-0,2512	2,2180	-2,0000	3,5000	54,8041
SHEL	O(E10o - E32o)	2868,00	51,93%	3,5718	0,0251	2,1369	2,0000	2,0000	54,4992
SHEL	(L2c + L22c + L27c) + O(S17c - S27c)	6563,00	55,20%	8,4254	0,1403	2,1342	-24,0000	6,4000	54,3100
SHEL	(S12o + S19o + S27o) + O(S17c - S27c)	5242,00	55,84%	6,7302	0,0606	2,1529	18,0000	6,5000	54,5460
SHEL	(L2c + L22c + L27c) + O(L22c - L27c)	5324,40	54,56%	6,8349	0,0716	2,1490	-24,0000	4,5000	54,5330
XOM	(E2o + E22o + E47o)	13,04	49,11%	0,0233	0,7116	5,8792	-0,7800	-0,0400	1,8915
XOM	O(S38c - S7c)	95,65	51,68%	0,1070	0,6351	3,9139	-0,0500	0,0650	1,9198
XOM	O(S6o - S28o)	90,92	52,21%	0,1006	0,5805	3,9317	0,6700	0,0700	1,9151
XOM	O(S16o - S28o)	95,28	51,55%	0,1054	-0,2965	4,1218	0,2800	0,0700	1,9149
XOM	(E2o + E22o + E47o) + O(S16o - S28o)	105,44	50,00%	0,1141	0,6047	3,9503	-0,0800	0,0050	1,9021

Notes: E — exponential moving average, S – simple moving average, L – linear weightedmoving average, o – moving average is built based on opening prices, c – moving average is built based on closing prices, O – oscillator, S28 and so on – period of moving average, Mx – average reslut, As – asymmetry of the result, Exc – kurtosis of the result, Mo – mode of the result, Me – median value of the result, Std – standard deviation of the result.
Source: compilled by authors

A comparison of our results to those of the 'buy and hold' method, displayed in Table 6 below.

Table 6. The result of the "Buy and hold" strategy for test periods

Ticker	Entry date	Entry price	Exit date	Exit price	Result, $
BP	23.12.2001	530	31.12.2017	493,19	-36,81
CVX	08.10.2000	42,41	31.12.2017	127,61	85,2
SHEL	17.07.2005	1748	27.12.2020	1286,2	-461,8
XOM	21.05.2000	41,19	31.12.2017	86,73	45,54

Source: compilled by authors

As we can see, the "Buy and hold" strategy is not profitable on the test period for all assets. For those assets where it does generate profit, it is lower compared to most of the selected strategies, except for:
1) CVX, strategy (S5c + S24c + S50c), with a total accumulated result of $59,83;
2) CVX, strategy (L2c + L14c + L55c), with a total accumulated result of $54,43.

Strategy verification. To verify the models, 2 models based on moving average combinations, 3 models based on oscillators, and 3 models combining moving averages and oscillators were taken. It should be noted that for the asset XOM, there was only one moving average combination that generated profit, and it was used further for system verification. Accordingly, only one combination of moving averages and oscillators was selected for the asset XOM. The results of the verification of the selected trading strategies are shown in Table 7.

Table 7. System verification results

Ticker	Indicators combination	Result, $	Forecast correctness	Mx	As	Exc	Mo	Me	Std
BP	(S9c + S18c + S43c)	34,03	50,24%	0,1660	0,0173	4,2050	-3,8000	0,1300	15,5489
BP	(S7o + S15o + S40o)	113,09	29,13%	0,3168	0,2396	9,4797	0,0000	0,0000	12,0607
BP	O(E4c - E20c)	-27,27	50,14%	-0,0764	0,2912	3,5251	7,0000	0,1100	14,5485
BP	O(S15o - S32o)	-380,81	47,06%	-1,0667	-0,1725	3,5055	-7,0000	-0,8900	14,5095
BP	O(S18c - S43c)	29,37	49,30%	0,0823	0,5619	3,5061	-11,8900	-0,1100	14,5485
BP	(S9c + S18c + S43c) + O(S15o - S32o)	233,69	51,26%	0,6546	0,1089	3,5131	7,0000	0,4900	14,5340
BP	(S7o + S15o + S40o) + O(S15o - S32o)	181,49	52,10%	0,5084	0,1199	3,5103	5,7500	0,6000	14,5398
BP	(S9c + S18c + S43c) + O(S18c - S43c)	96,81	51,54%	0,2712	0,1495	3,5099	-11,8900	0,5200	14,5462
CVX	(S5c + S24c + S50c)	-41,59	41,76%	-0,2446	0,0122	3,3029	-0,8500	-0,7150	4,9755
CVX	(L2c + L14c + L55c)	-55,12	39,20%	-0,3132	0,5964	2,7750	4,3300	-0,8200	4,6202
CVX	O(S49o - S8o)	-96,60	46,22%	-0,2706	0,2456	3,4662	2,2200	-0,4700	4,6000
CVX	O(L4o - L25o)	-41,90	51,82%	-0,1174	0,0105	3,3900	-2,2200	0,1500	4,6064
CVX	O(S6c - S24c)	30,70	54,62%	0,0860	0,0630	3,3821	0,7500	0,4500	4,6071
CVX	(S5c + S24c + S50c) + O(L4o - L25o)	-31,44	47,34%	-0,0881	0,0700	3,3924	-2,2200	-0,2800	4,6071
CVX	(L2c + L14c + L55c) + O(S6c - S24c)	27,28	47,34%	0,0764	0,7961	3,3330	0,7500	-0,2800	4,6073
CVX	(S5c + S24c + S50c) + O(S6c - S24c)	27,14	50,14%	0,0760	0,0987	3,3798	0,7500	0,0200	4,6073
SHEL	S(12o + 19o + 27o)	-649,35	48,51%	-4,8459	-0,7275	3,6289	-51,4000	-3,1900	65,7619
SHEL	(L2c + L22c + L27c)	-487,88	43,22%	-4,1346	0,3665	0,0043	25,8000	-15,9000	64,9699
SHEL	O(S17c - S27c)	1198,97	52,00%	5,9949	-0,1646	2,3376	56,0000	1,8750	67,3119
SHEL	O(E10o - E32o)	-1461,97	44,00%	-7,3099	-0,4887	2,0791	-56,0000	-7,5950	67,1818
SHEL	O(L22c - L27c)	-319,43	48,00%	-1,5972	-0,0903	2,2363	-51,4000	-3,0950	67,5594
SHEL	(L2c + L22c + L27c) + O(S17C - S27c)	-156,59	44,50%	-0,7830	0,0982	2,2478	-51,4000	-9,1700	67,5738
SHEL	(S12o + S19o + S27o) + O(S17c - S27c)	-47,85	48,50%	-0,2393	-0,4150	2,2366	-51,4000	-3,0950	67,5779

Ticker	Indicators combination	Result, $	Forecast correctness	Mx	As	Exc	Mo	Me	Std
SHEL	L(2c + L22c + L27c) + O(L22c - L27c)	-420,55	44,50%	-2,1028	0,1220	2,2623	-51,4000	-10,2750	67,5456
XOM	(E2o + E22o + E47o)	63,33	54,50%	0,2853	0,0513	0,9188	-0,3900	0,2200	2,9707
XOM	O(S38c - S7c)	68,55	50,83%	0,1904	0,2437	1,2976	0,3900	0,0700	2,8743
XOM	O(S6o - S28o)	35,17	50,56%	0,0977	0,3357	1,3081	0,3900	0,0500	2,8789
XOM	O(S16o - S28o)	16,63	51,39%	0,0462	-0,1818	1,3635	-0,3900	0,0850	2,8802
XOM	(E2o + E22o + E47o) + O(S16o - S28o)	40,09	53,61%	0,1114	-0,1361	1,3763	-0,3900	0,1800	2,8784

Source: compilled by authors

Thus, as a result of the verification, we established:

1) for the asset BP:

a) the feasibility of using the combination of moving averages and an oscillator (S9c + S18c + S43c) + O(S18c - S43c) with a result of $96.81 USD/share is confirmed. Moreover, the result of the combination is higher than the sum of the results of the component systems;

b) the effectiveness of using the combination of moving averages (S9c + S18c + S43c) with a result of $34.03 USD/share is confirmed;

c) the effectiveness of using the oscillator, which demonstrated the best result on the test period, is not confirmed;

2) for the asset CVX:

a) the feasibility of using the combination of moving averages and an oscillator (L2c + L14c + L55c) + O(S6c - S24c) with a result of $27.28 USD/share is confirmed. The result of the combination is higher than the sum of the results of the component systems;

b) the effectiveness of using the combination of moving averages and the oscillator, which demonstrated the best results on the test period, is not confirmed;

3) for the asset SHEL:

a) the feasibility of using the combination of moving averages and an oscillator, as well as only the combination of moving averages, which demonstrated the best results on the test range, is not confirmed;

b) however, the effectiveness of using the oscillator O(S17c - S27c) with a result of $1198.97 USD/share is confirmed;

4) for the asset XOM:

a) overall, the effectiveness of using the combination of moving averages and an oscillator (E2o + E22o + E47o) + O(S16o - S28o) with a result of $40.09 USD/share is confirmed. However, the result is lower than the sum of the component systems;

b) in turn, the effectiveness of using the combination of moving averages (E2o + E22o + E47o) with a result of $63.33 USD/share is confirmed;

c) the effectiveness of using the oscillator O(S38c - S7c) with a result of $68.55 USD/share is also confirmed.

We can now benchmark our findings against the “Buy and hold” performance, detailed in Table 8.

Table 8. The result of the "Buy and hold" strategy for verification periods

Ticker	Entry date	Entry price	Exit date	Exit price	Result, $
BP	07.01.2018	527,7	03.11.2024	372.93	-154,77
CVX	07.01.2018	127,86	03.11.2024	156,75	28,89
SHEL	03.01.2021	1300,8	03.11.2024	2608,48	1307,68
XOM	07.01.2018	86,72	03.11.2024	118,39	31,67

Source: compilled by authors

As we can see, the "Buy and hold" strategy is profitable on the verification range for all assets except BP. Compared to the best combined strategies, the results are as follows:

1) for the asset BP, the strategy (S9c + S18c + S43c) + O(S18c - S43c) is more effective;

2) for the asset CVX, the "Buy and hold" strategy is 5.90% more effective compared to the combined strategy;

3) for the asset SHEL, the "Buy and hold" strategy is 9.07% more effective compared to the calculated strategy;

4) for the asset XOM, the strategy (E2o + E22o + E47o) + O(S16o - S28o) is 17.46% more effective compared to "Buy and hold".

Despite this, it should be taken into account that the selected strategies based on indicators were also profitable in the test period, where the "Buy and hold" strategy demonstrated worse results for the specified models. Accordingly, an economic agent who would make a decision about resource allocation at the beginning of the verification period would not have absolute certainty about the possible outcome of the "Buy and hold" strategy. Therefore, combined strategies can be considered as providing effective resource allocation.

Discussion. Although time series modeling techniques are widely used in pricing research, there remains a limited number of studies examining the predictive capabilities of multi-factor models incorporating diverse variables. On the basis of the conducted research, author identified that the stock price forecasting system for oil companies based on oscillatory indicators, that helps an agent to define flat period on the market, and enhanced by combinations with trend indicators during periods of directional market forces could be used by economic agent in order to achieve efficient resource allocation.

Conclusion. The conducted research provides grounds for the following conclusions:

1) combinations of technical indicators can be used as effective tools for forecasting changes in stock prices of companies in the oil and gas industry;

2) by using combinations of technical indicators over a long-term period to make decisions about resource allocation, an economic agent achieves higher efficiency compared to using a single specific indicator;

3) however, both the indicators used to build the forecasting system and the indicator settings need to be selected and tested for each instrument separately. Universal settings cannot be applied not only to companies of the same industry in different countries but also to companies within the same country;

4) one reason for this is that the prospects of different companies, even within the same industry, are perceived differently by the stock market, depending not only on the company's performance but also on fundamental factors. Accordingly, stock exchange participants, in order to achieve their goals, place exchange orders with different periods and execution volumes, which immediately affect the quotations.

Accordingly, we see the following as directions for further research:

1. Development of new indicators or indicator systems: The goal would be to create tools that can proactively identify the onset of changes in price behavior (or shifts in market sentiment) and translate these changes into actionable trading signals.

2. Automation of calculations and machine learning: This involves using programming languages to automate the calculations and building machine learning algorithms based on the proposed algorithms.

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