8 OPTIMIZING ALGORITHMIC TRADING STRATEGIES FOR EMERGING MARKETS: EVIDENCE FROM ESG-FOCUSED STOCKS IN BORSA ISTANBUL

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Abstract

Today, algorithmic trading (AT) plays a crucial role in financial forecasting. This study explores AT strategies for an emerging market, Borsa İstanbul (BIST). Analyzing Environmental, Social, and Governance (ESG)-focused stocks from the BIST Sustainability Index, a robotic trading algorithm implemented in C# optimizes trading parameters for return. Key technical indicators; Relative Strength Index (RSI) and Simple Moving Average (SMA) evaluate trends and improve decisions. Results show longer timeframes achieve higher profitability, while shorter intervals face volatility. The study underlines the potential of tailored AT strategies in emerging markets, offering insights for small investors to manage risk and return. Findings emphasize the role of local market dynamics in building robust, algorithm-driven trading solutions.

Keywords: *Financial Forecasting, Emerging Markets, Investment Decisions, Sustainability Index, Technical Indicators*

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1. Introduction

In his classic finance book named A Random Walk Down Wall Street, Malkiel (2019, p.26) describes the random walk as a behavior pattern in which future steps cannot be predicted based on past actions. When this term is applied to the stock market, it means that short term changes in stock prices are highly unpredictable. Accurately predicting the future path of stock prices and identifying the optimal timing for buying and selling are among the most challenging decisions for investors. Because investors expect high returns. To date, various methods have been developed, however, most investors tend to rely on either technical or fundamental analysis.

Technical analysis is a method aimed at predicting the optimal timing for buying and selling, fundamentally based on the creation and interpretation of stock charts. It involves examining the past to forecast the future consistently, focusing on tracking fluctuations in stock prices and

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trading volumes. On the other hand, fundamental analysis aims to determine the appropriate price of a security. In this case, factors such as value, growth, dividends, repayment, interest rates, and risk are considered. Fundamental analysts make judgments about a stock's value by forecasting factors like the company's future growth rate. When this value is above the market price, they recommend buying the stock to investors.

Different mathematical, statistical, and Artificial Intelligence (AI) methods support investors for better and more consistent predictions (Samitas *et al*., 2020; Chhajer *et al*., 2022; Song and Jain, 2022). There are different views among academics and financial professionals regarding AI's ability to outperform the stock market. Because of AI's superior capacity for calculations and data processing, especially with large datasets, many people believe that with further advancements in technology, AI will eventually dominate the market, if not already yet. According to two major financial theories: the Random Walk Model by Fama *et al*. (1969) and the Efficient Market Hypothesis by Fama (1965; 1970), stock prices are influenced by new information that cannot be predicted through traditional stock market analysis. An AI-based investment strategy focused solely on technical analysis of historical data cannot outperform the stock market, as stock prices have already fully incorporated this information (James, 2023).

It's important to define the role of AI in the stock trading process in order to stress the efficiency of it. In an AI-driven investment approach, asset managers use natural language processing (NLP) tools to analyze large volumes of news and social media content. This technique, known as "sentiment analysis", helps predict investor sentiment about specific companies, potentially enabling AI-driven strategies to develop more informed investment plans and outperform traditional investment methods (Day and Lee, 2016; Gurrib and Kamalov, 2022). AI-based investment strategies go beyond passive sentiment analysis. As demonstrated in the final US presidential election, Brexit Referendum campaign, COVID-19 pandemic, GameStop manipulation even highly intelligent individuals can be swayed by false or misleading social media posts on platforms like Meta and X, leading to significant consequences for society. Therefore, it's not surprising that AI-driven strategies might become more aggressive in actively influencing investor expectations about the stock market. Additionally, there could be other trading strategies with the potential to outperform historical averages (Song and Jain, 2022). For example, Batten *et al*. (2022) showed that the treasury-eurodollar spread and macroeconomic uncertainty measures can predict the US equity premium more accurately than the historical average during different business cycles. Ultimately, if AI can simulate these strategies earlier and more effectively than traditional investors, in terms of the investment world the Darwinian theory of "Survival of the fittest" could transform into "Survival of the Smartest", where the smartest AI would claim the ultimate victory in the investment game (Song and Jain, 2022).

Latest studies indicate that stock market analysis methods are divided into two groups as mathematical and AI-based techniques. Mathematical approaches involve statistical tools, while AI methods are centered around machine learning (ML) algorithms (Januschowski *et al*., 2020). It has been noted that the majority of the studies reviewed categorize broadly stock price prediction techniques into two groups. The first one is Traditional ML algorithms and the other one is Deep Learning (DL) and Neural Networks (NN) (Soni *et al*., 2022). However, there are various ML, DL, and NN methods available to predict stock prices. A key ongoing debate in stock price prediction is which methods are most commonly used to foresee stock prices (Lin and Margues, 2024).

Stock trading is a challenging decision-making process that requires forecasting market price movements. Thus, analyzing the performance of numerous algorithms is essential to conduct extensive market analysis and maximize investors' financial returns aiming at buying at low prices and selling at high prices. For this purpose, an array of financial data sources and services have been used for predicting stock trading signals in this study. The goal is to provide valuable practical insights to investors on algorithm selection, balancing risk and return, and making more informed investment decisions. Another key point regarding to return prediction is the market that we are in. Each stock market has its unique characteristics shaped by its history and development, resulting in distinct prediction challenges and methods. Our research focuses on the Turkish stock market, Borsa İstanbul (BIST), for three main reasons. First, BIST has experienced remarkable growth, both in the number of listed companies and its overall market size, garnering increasing interest from investors and researchers worldwide. Second, as a developing market, BIST is characterized by fluctuations and gaps inherent to its growth phase. For example, the predominance of domestic investors contributes to higher market volatility. Third, recent government-led reforms aim to restructure the stock market, potentially introducing new dynamics and opportunities for analysis. These factors highlight the need to reassess the challenges of return prediction within the context of the Turkish stock market.

This study aims to guide small investors in developing and selecting investment strategies through algorithmic trading (AT) in the Turkish stock market, optimizing trading parameters for maximum profit while minimizing risk. It focuses on applying a method that protects investors and is accessible to everyone. Also, the research conducts an in-depth analysis of the impact of both individual and combined indicators in AT.

Here are the key contributions and novelties of the paper:

1. The paper focuses on the Turkish stock market, BIST. While most studies (Pun and Wong (2019), Carta *et al*. (2021) and Khan *et al*. (2022)) concentrate on larger and more developed markets, examining the dynamics of an emerging market like BIST and its impact on AT can address the knowledge gap in this area.
2. The study aims to develop AT strategies tailored to small investors, providing practical tools and methods to enhance their decision-making and risk management capabilities. This could add a new perspective to the literature, which often focuses on large institutional investors.
3. Analyzing local characteristics of BIST, such as market volatility, risk, listed companies, portfolio optimization, trading strategies and investor profiles can support the adaptation of global models to local dynamics and the development of localized market strategies in the literature.
4. The study aims to provide a guide for optimizing the risk-return balance in algorithm selection, contributing to the literature on developing practical approaches for optimizing investment decisions.

The paper is organized as follows. Section 1 begins with an introduction to the research objectives and context. Section 2 offers a widely literature review. Section 3 details the material and method process. Section 4 presents the experimental findings alongside a discussion. Finally, Section 5 concludes the study and provides recommendations for future research.

2. Literature Review

Recent studies have highlighted the effectiveness of ML and DL techniques in the stock market. AT systems utilizing these methods can detect patterns in market data and uncover profitable trading strategies, resulting in enhanced performance. This section reviews recent studies on the literature, showcasing the potential of advanced technologies in optimizing stock trading.

To enhance AT, the paper by Bajaj and Aghav (2016) focused on developing AT strategies tailored for Indian Stock Index options, with an emphasis on using technical indicators such as Relative Strength Index (RSI), Moving Averages, and Average True Range. The primary goal was to optimize trading parameters for maximum profit and minimum risk via various entry and exit strategies. The study demonstrated that applying technical analysis to index option trading resulted in stronger risk-adjusted returns through diversified strategies. However, despite the high profit-to-risk ratio, the system performed poorly in volatile market conditions, leading to significant losses and potential debt, as the drawdown exceeded the initial capital. Additionally, the study's focus on individual indicators, rather than combining them, contributed to the low accuracy of the results. Qiu and Song (2016) tackled the challenge of predicting stock market index movements, a topic of significant research due to the impact of factors such as political events, economic conditions, and trader expectations. Their study compared two types of input variables to predict the daily direction of the Japanese stock market index, employing an optimized artificial neural network (ANN) model. By integrating genetic algorithms to enhance the ANN model, the study achieved improved prediction accuracy, illustrating that the careful selection of input variables can significantly enhance forecasting performance compared to prior research.

Lee *et al*. (2020) applied Long Short-Term Memory (LSTM) deep neural networks using only technical indicators to foresee share prices for the Taiwan Stock Exchange, achieving a 75% prediction accuracy. Similarly, Parray *et al*. (2020) utilized technical indicators and historical price data with neural networks to forecast stock prices for the NSE NIFTY50, reaching a prediction accuracy of 76%.

Srivastava *et al*. (2021) analyzed a dataset consisting of trading signals and normalized technical indicators, covering daily historical prices from the beginning of 2013, to end of June, 2020, spanning 7.5 years and 1,725 data points. The dataset was divided into training with 1,380 points and testing with 345 points. The study utilized various ML techniques. Among those, the results showed that Gradient Boosting outperformed Random Forest (RF). While the focus was on the Indian stock market and index predictions, the study did not incorporate AT or technical indicators, limiting itself to market prediction. Another study by Xia *et al*. (2021) focused on time series prediction in financial markets, a growing area of interest for both investors and researchers. They introduced a forecasting framework that integrates wavelet coherence, multiscale decomposition, and Support Vector Regression (SVR). To enhance prediction accuracy for complex, multidimensional data, SVR was applied after a preprocessing step that extracted key information from the raw data. The performance of the framework was evaluated through comparative experiments on the Dow Jones Index and the Shanghai Composite Index. The importance of various technical indicators, including Moving Average Convergence/Divergence (MACD), RSI and On-Balance Volume (OBV), was examined by Salkar *et al*. (2021). The authors concentrated on the US market. To verify their approach, the researchers developed and tested multiple trading strategies using these technical indicators. They explored combinations of two indicators at a time, such as MACD and RSI, MACD and OBV, and OBV and RSI. However, their strategies yielded only a 12% profit, suggesting that further research into different indicator's combinations is necessary to increase profit margins.

Bhandari *et al*. (2022) developed a predictive model using a LSTM neural network to forecast the next day's closing price of the S&P 500 index, selecting nine key predictors, including market data, macroeconomic indicators, and technical metrics. Their findings showed that the single-layer LSTM model outperformed multi-layer models in terms of prediction accuracy. Frattini *et al*. (2022) introduced the TI-SiSS trading algorithm combining technical indicators with NLP based metrics from unusual data sources such as news and social media. The algorithm, tested on 527 companies (91% based in the USA) from September 25, 2019, to February 18, 2022, outperformed single-threshold methods, achieving a maximum return of 1.15% and ranking highest in the Sharpe ratio. However, their limitations imply its reliance on historical data, potential overfitting, and uncertainties regarding the applicability of the results to various market conditions.

Cakici *et al*. (2023) explored stock return predictability using ML across 46 global stock markets, incorporating 148 firm characteristics as input variables for various models. The models successfully utilized factors like momentum, reversal, value, and size to generate substantial economic gains, especially when these factors were combined. However, their performance was influenced by factors such as firm size, the availability of recent data, and market-specific conditions like the number of listed firms and idiosyncratic risks, which limited arbitrage opportunities. The performance of four technical indicators was evaluated by Prashanth *et al*. (2023); Bollinger Bands (BB), Exponential Moving Average (EMA), Parabolic Stop and Reverse (PSAR), and RSI using Bitcoin price data between 2018-2022. They developed four different strategies. Testing these strategies on five years of Bitcoin price data resulted in substantial profits of 154%, 437%, 256%, and 701%, respectively. While these results underline the volatility of the cryptocurrency market and its potential for high profits, they may not be replicable in markets like the Indian Stock Exchange. The study's limitation lies in the use of individual indicators rather than exploring combinations, suggesting the need for further research on combined indicator strategies. To tackle the challenges of predicting stock market trends, Pagliaro (2023) introduced a classification-based approach to enhance return predictions by minimizing forecasting errors. The study utilized the Extra Trees Classifier (ETC) to predict stock returns, with technical indicators as input variables. The goal was to calculate the percentage change between the closing price and the closing price 10 trading days later for 120 companies across different sectors. The results showed that the ETC model achieved an accuracy of 86.1%. Supsermpol *et al*. (2023) developed foresightful models for post-Initial Public Offering (IPO) financial performance using a dataset of 134 companies listed on Thailand stock market, covering financial measures and IPO-related information from 2002 to 2021. The study found that while logistic regression achieved an accuracy of 61.94%, RF models outperformed with an accuracy of 72.14% and an AUC of 0.8416, though further exploration is needed for real-world application.

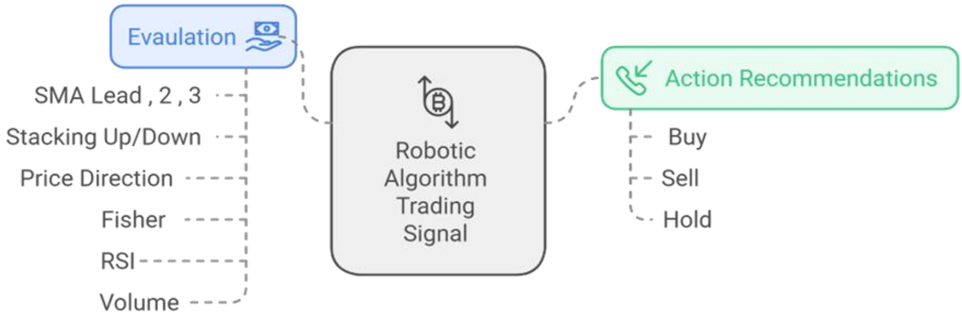
To improve decision making process for predicting market movements the work presented by Park *et al*. (2024) introduced the Deep Q-Network Action Instance Selection (DAIS) trading system, which combines reinforcement learning with instance selection to address noisy stock price data and enhance trading performance. Evaluated using data from 72 KOSPI-listed companies, DAIS outperformed previous supervised and reinforcement learning systems, demonstrating its efficiency in stock trading. Mengshetti *et al*. (2024) integrated four key indicators; Volume-Weighted Average Price (VWAP), RSI, MACD and EMA in order to develop a strategy called "Weapon Candle," a robust trading approach. Backtesting on the Indian stock market revealed a profit factor of 1.882 and 61% profitable trades, outperforming strategies using fewer indicators. The results highlight the effectiveness of combining multiple technical indicators for more accurate trading signals, offering algorithmic traders a comprehensive tool for informed market decisions. Wang *et al*. (2024) investigate return prediction in the Chinese stock market using the Augmented Tree-Based Conditional Sort (ATBCS) method, analyzing monthly data from over 5,000 stocks between January 2005 and December 2022. Their findings reveal a shift from a reversal effect (pre-2018) to a momentum effect (post-2018), attributed to the growing influence of institutional investors. The momentum strategy achieves an annual excess return of 10.60%, consistently outperforming the market portfolio.

3. Material and Method

In this study, an array of financial data sources and services were used to conduct extensive market analysis and algorithmic trading. A robotic trading algorithm was written using C# and was executed on the MatriksIQ Algo platform to automate the trading strategies.

The following tools and resources were utilised to collect data and implement the strategy. MatriksIQ Data Terminal offered real-time access to a variety of market data, including stock prices, indexes, and other financial instruments. It was necessary to monitor and analyse high-frequency market movements, as well as collect historical and current transaction data for the chosen companies. IQ Algo was used to automate and carry out trading methods under predefined conditions. It made it easier to create and backtest complex strategies for usage in real-time market situations. *BIST Hisse 10. Kademe Derinlik* provided a 10-level order book depth for equities listed on the BIST. It was used to assess market liquidity and understand the underlying supply and demand dynamics for the chosen shares, hence assisting decision-making. *BIST Endeksleri* represented broader market trends and was used to assess sector performance and link individual stock movements to overall market conditions. This tool provides a macroeconomic framework for optimising trading strategies. *BIST Anlık Fiyat (Hisse/VIOP)* provided real-time price feeds for stocks and VIOP (BIST Futures and Options Market), facilitating speedy trade execution. It was notably useful in high-frequency trading environments, guaranteeing that data was current and responsive within milliseconds. Figure 1 illustrates the main parameters for the stock price evaluation system framework.

Figure 1. Main Parameters for the Price Evaluation Process



All data sources were combined into a single platform, enabling for seamless analysis, backtesting, and execution of trading strategies over a variety of time periods. The tools were chosen based on their accuracy, dependability, and capacity to support sophisticated, algorithm-driven trading strategies.

3.1. Stock Selection and Data Collection

Corporate sustainability refers to the integration of Environmental, Social, and Governance (ESG) principles into a company's activities and decision-making processes to create long-term value while managing risks arising from these areas.

In Türkiye, and particularly among BIST companies, the BIST Sustainability (XUSRD) index has been established to enhance awareness, knowledge, and practices regarding sustainability. It includes shares of companies listed on BIST that demonstrate superior corporate sustainability performance. The XUSRD Index has been calculated since November 4, 2014, based on the idea that it serves a critical mission by guiding companies in developing policies on ESG risks and providing information on these policies to responsible investors. 84 shares listed in the XUSRD Index as of December, 2024, are selected by following criteria (BIST, 2024):

- Companies with an overall sustainability score of 50 or above,
- Scores of at least 40 in each main category,
- At least eight category scores of 26 or above.

This study examines the profitability of the algorithm for stocks listed in the XUSRD Index over various timeframes. To ensure a diverse and unbiased analysis, stocks such as KCHOL, TCELL, and VAKBN were selected, representing the holding, communication, and banking industries, respectively. These stocks were chosen randomly rather than based on specific strategic criteria, ensuring neutrality in the evaluation process. Their selection also reflects the aim to cover key industries with significant market presence, making them representative of their respective sectors. Furthermore, the study investigates the industrial distribution and preferences of these chosen stocks, alongside the correlation and alignment of various industries with the XUSRD index, to assess performance trends and interconnections.

The timeframes included daily, 120-minute, 240-minute, and 60-minute intervals. Shorter intervals (30 and 15 minutes) were omitted due to low data availability. Furthermore, TTRAK was excluded since its performance varied significantly from the overall patterns observed in the other stocks. Although it was excluded from the main analysis due to its performance deviating significantly from the general patterns observed in other stocks, it was included in the graphical representations for completeness. By incorporating TTRAK in the visuals, the study aims to provide a broader perspective, allowing readers to observe its distinct behavior compared to the other stocks. This inclusion helps to highlight the contrast and enrich the analysis, even though it was not a focal point of the profitability assessment.

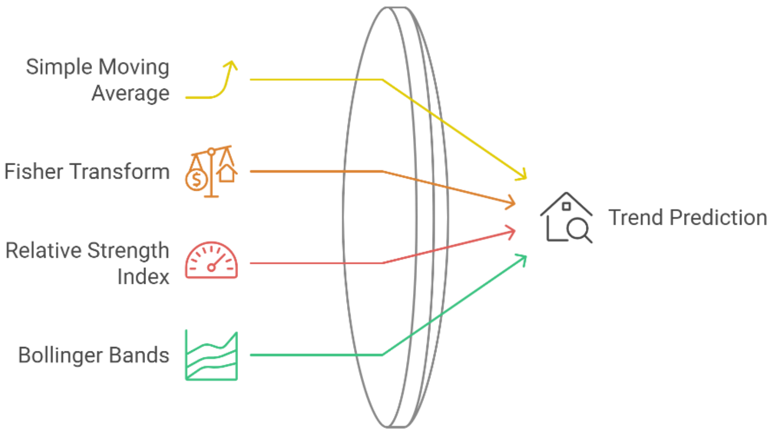
The statistics were derived from historical price datasets, which included opening, closing, high, and low prices for each time period, assuring consistency across all intervals. Equation 1 is used to calculate buy/sell price for each period.

$$Price = (Low + High + 2\ x\ Close)\ /\ 4 \tag{1}$$

3.2. Technical Indicators and Analytical Framework

To enhance the analysis, various technical indicators were employed to evaluate market trends and behavior. The Simple Moving Average (SMA) was applied to smooth price data, revealing underlying trends over different time periods. The Fisher Transform (FT) normalized price swings, providing clear signals of overbought and oversold conditions, especially during volatile market phases. The RSI served as a momentum oscillator, measuring the speed and magnitude of price changes to identify potential reversal points. Bollinger Bands (BB) were utilized to analyze price volatility, with the band width and period customized for each timeframe to effectively capture price breakouts and consolidations. The technical indicators outlined in Figure 2 were integral to enhancing the study of stock performance.

Figure 2. Technical Indicators Used for Price Predictions



These indicators were included in the performance study to help understand the underlying price movements and trading opportunities. The performance and profitability measures were primarily concerned with calculating the profit/loss percentage over various timeframes. In addition to measuring overall profitability, the analysis looked at profitability trends across different time periods to compare the efficacy of long-term versus short-term trading methods. Furthermore, the relationship between trade count, commission charges, and net profitability was examined, emphasising the importance of transaction frequency and associated expenses in overall performance.

3.3. Data Processing and Visualization

The dataset was preprocessed to ensure consistency and reliability. Stocks or intervals containing missing or abnormal data points were eliminated from the analysis. Following this phase, the processed data was analysed and visualised to find trends and linkages more efficiently.

Preliminary results showed that longer durations, such as daily intervals, consistently resulted in increased profitability for all analysed equities. Shorter timescales, spanning from 60 to 240 minutes, revealed decreasing returns, indicating limitations in high-frequency or short-term trading methods. The incorporation of technical indicators added depth to the analysis. SMA and BB effectively emphasised trend stability and breakout potential, however the FT provided more precise signals for price reversals, especially during volatile periods. The RSI proved effective in spotting overbought or oversold positions, particularly in shorter timeframes. Figure 3 and 4 show screenshots of robotic trade software to predict the stock prices of XUSRD Index.

Figure 3. Trade Signals from the Robotic Trade Software,

a) buy (Green), b) sell (Red)

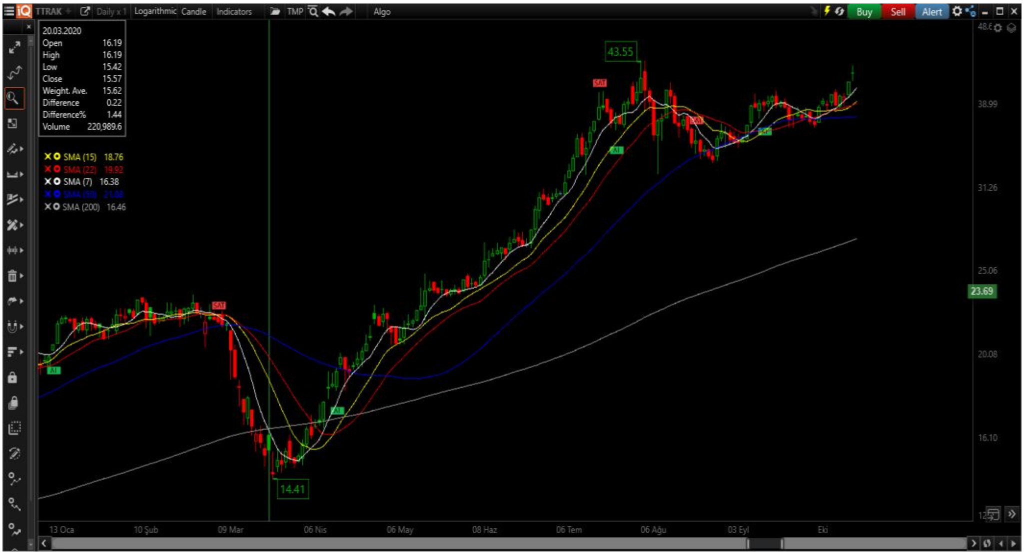
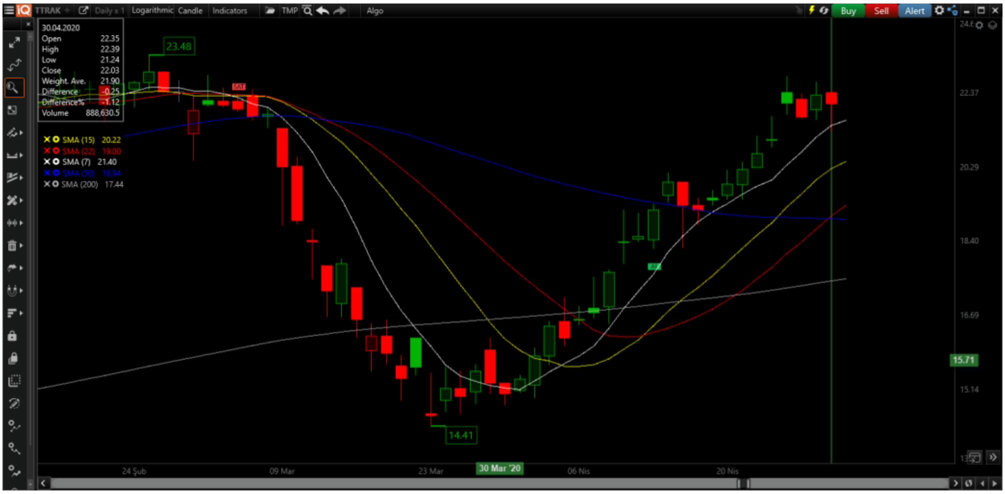


Figure 4. Robotic Trade Software



The trading method used in this study combines a number of technical indicators to improve decision-making and performance. Stacking up 7, 15, and 22 periods is utilised as a significant indicator for buying a company when there is upward momentum, and vice versa for selling when declining trends are noticed. The RSI acts as a corrective tool, balancing purchasing and selling power by identifying overbought and oversold levels, resulting in more precise entry and exit positions. The FT is used to evaluate trend reversals and identify probable market turning points. BB is used to identify extreme limits of market fluctuations, marking potential breakout or breakdown points. Finally, trade volume works as a confirmation mechanism, ensuring that signals created by the other indicators are backed up by adequate market activity. This multifaceted strategy seeks to increase the robustness and dependability of trading decisions.

4. Results and Discussion

Figures 5, 6, 7, 8 and 9 illustrate the changes in profit/loss percentages of selected stocks (XUSRD, TTRAK, KCHOL, TCELL, and VAKBN) across different timeframes.

Figure 5 illustrates the percentage profit/loss for XUSRD over various time intervals. The data shows the highest profitability in the daily period, followed by a decline in the 240-minute interval. There is a slight recovery in the 120-minute interval, but profitability decreases again in the 60-minute interval. No profit or loss is observed for the 30 and 15-minute intervals.

Figure 6 shows the percentage profit/loss for TTRAK over various time intervals. The data shows that profitability is highest in the daily period, followed by a slight decrease in the 240-minute interval, and then a modest increase in the 120-minute interval. However, profitability declines again in the 60-minute interval, and no profit or loss is observed for the 30 and 15-minute intervals.

Figure 5. Performance metrics for XUSRD

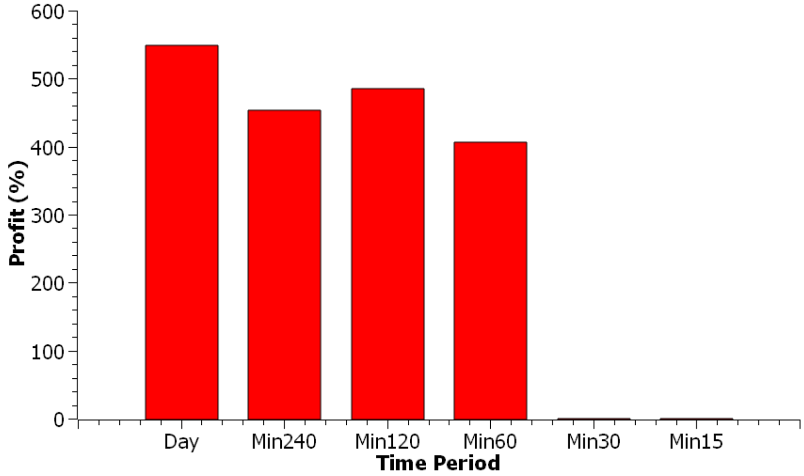


Figure 6. Performance metrics for TTRAK

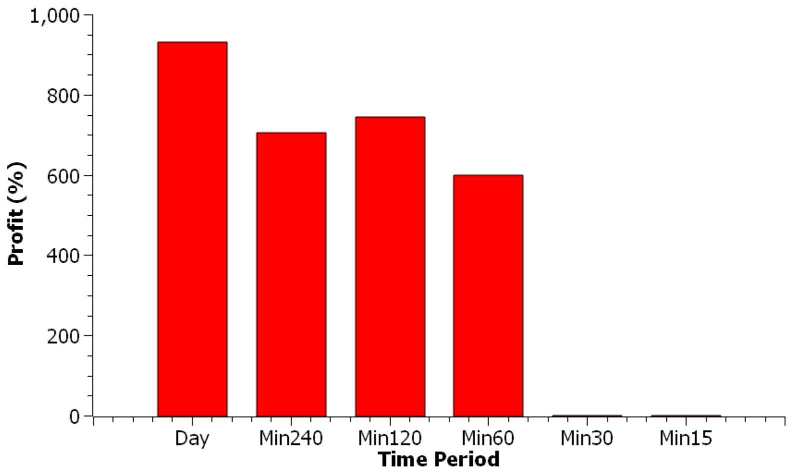


Figure 7 illustrates the percentage profit/loss for KCHOL over various time intervals. The data shows an increasing trend in profitability from the daily period to 240 and 120-minute intervals, peaking at the 120-minute interval. However, profitability decreases for the 60-minute interval, and no profit or loss is observed for the 30 and 15-minute intervals.

Figure 7. Performance metrics for KCHOL

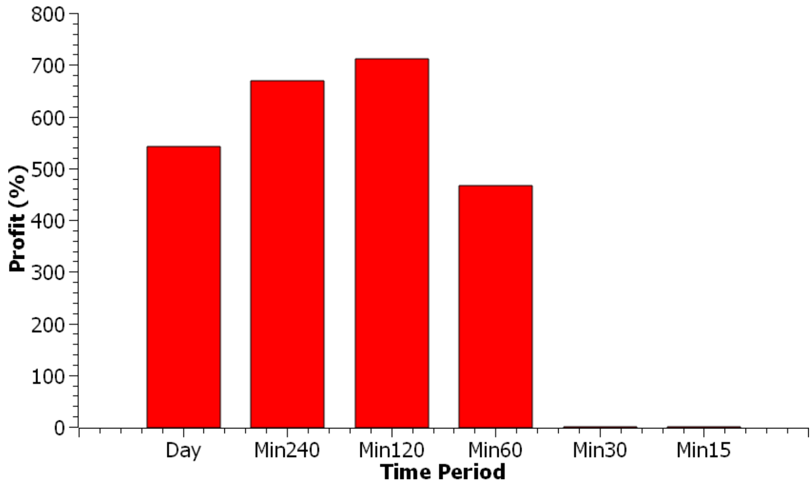


Figure 8 demonstrates the percentage profit/loss for TCELL over various time intervals. The data reveals a decreasing trend in profitability from the daily period to shorter timeframes (240, 120, and 60 minutes), while no profit or loss is observed for 30 and 15-minute intervals.

Figure 8. Performance metrics for TCELL

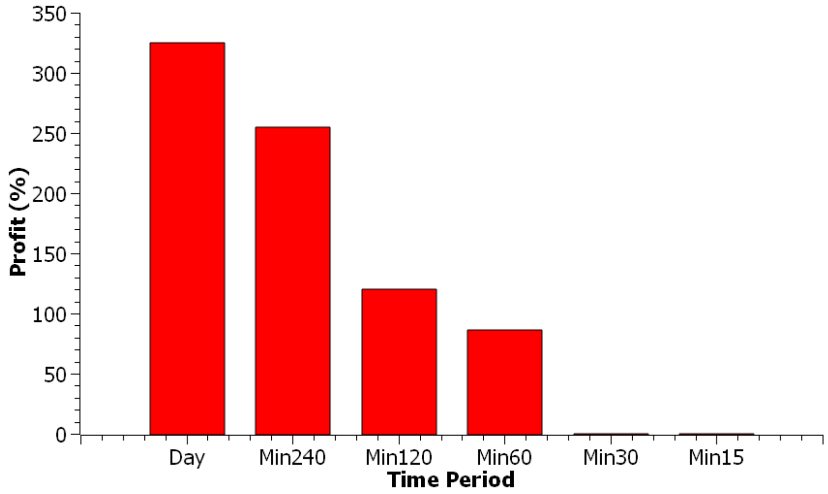


Figure 9. Performance metrics for VAKBN

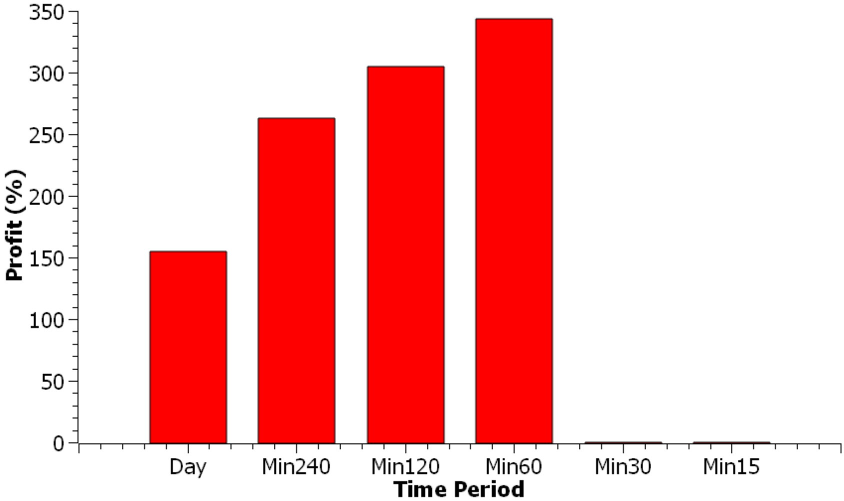


Figure 9 shows the percentage profit/loss for VKBNK over various time intervals. The data demonstrates an increasing trend in profitability from the daily period to shorter timeframes (240, 120, and 60 minutes), while no profit or loss is observed for 30 and 15-minute intervals.

The results reveal that all stocks achieved their highest profitability levels on day period. Notably, KCHOL demonstrated significantly higher performance than the others, with a profitability rate of 541.18% in daily period. XUSRD ranked second with a profitability of 444.45%, followed by VAKBN and TCELL and, which achieved 343.21% and 324.96% profitability, respectively.

As the timeframe shortened, a decline in profitability was observed across all stocks. For instance, in the 120-minute timeframe, KCHOL maintained a profitability of 669.30%, while XUSRD, TCELL, and VAKBN achieved 484.60%, 254.56%, and 304.76% profitability, respectively. A similar downward trend continued in the 240-minute and 60-minute timeframes. This trend suggests that shorter-term trades tend to yield lower profitability, while daily long-term trades offer more advantageous outcomes. Among the stocks, KCHOL consistently exhibited the highest performance across all timeframes. XUSRD, on the other hand, managed to maintain relative stability in profitability, particularly in shorter timeframes, compared to the other stocks.

Figure 10 illustrates the average operation counts for the examined stocks. It highlights that the average commission follows a similar distribution pattern, indicating a steady relationship between operation counts and commission averages across the dataset.

These results indicate that long-term trading strategies offer greater profitability potential, while short-term trades may have limited returns. The declining trend in short-term strategies can be considered a reflection of the risks associated with high-frequency trading. This analysis provides important insights into the impact of timeframes on trading strategies.

The performance results obtained indicate the percentage profit/loss for five selected stocks over various time intervals. The data shows that profitability is highest in the daily period for all stocks, followed by varying trends across shorter timeframes. A general decline is observed as the intervals shorten from 240 minutes to 60 minutes, with no profit or loss recorded for the 30 and 15-minute intervals.

Figure 10. Operation Counts for Stocks

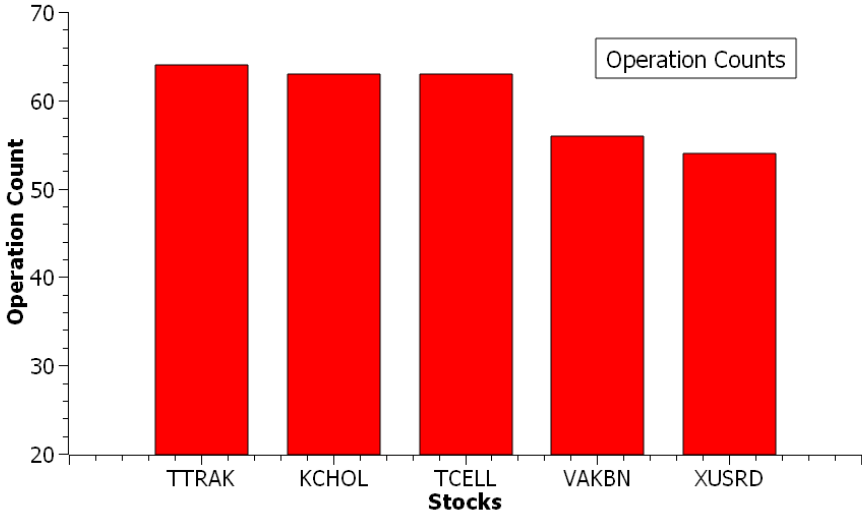
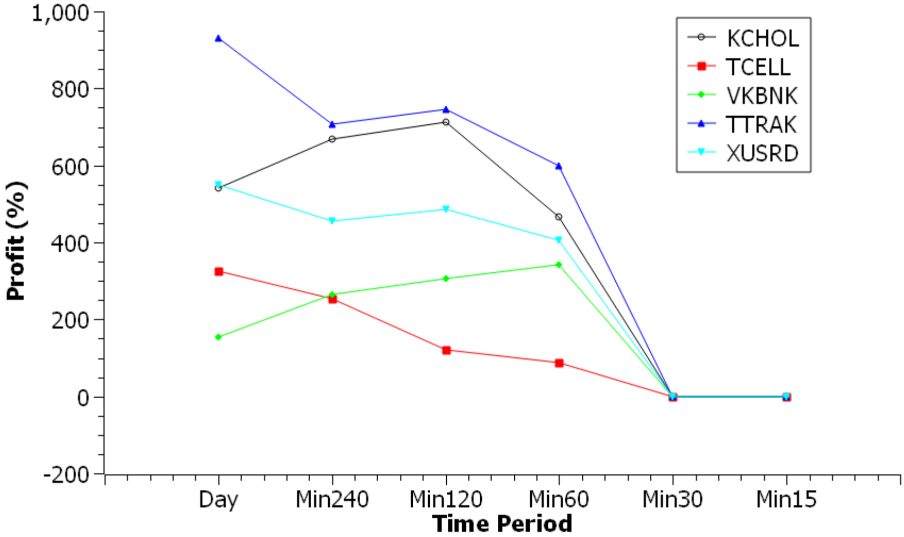


Figure 11 illustrates the percentage profit/loss for five selected stocks (KCHOL, TCELL, VKBNK, TTRAK, and XUSRD) over various time intervals. The data reveals that the best profitability is observed in the daily period, with TTRAK leading at 930.65%, followed by KCHOL at 541.18%, and XUSRD at 548.61%. In contrast, the least profitability is recorded for the 30-minute and 15-minute intervals, where all stocks show zero profit or loss.

Figure 11. Profitability Trends Across Timeframes



When examining the shorter time intervals, a general decline in profitability is observed. For example, in the 240-minute timeframe, KCHOL showed a profit of 669.30%, while TCELL achieved 254.56%, and VKBNK recorded 263.18%. In the 120-minute timeframe, KCHOL maintained a profitability of 711.61%, the highest across all stocks in this interval, while the other stocks experienced moderate declines.

These trends suggest that shorter-term trades (240 and 120-minute periods) yield lower profitability compared to daily trades, which offer more favorable outcomes. Among the stocks, KCHOL consistently exhibited strong performance across all timeframes, while XUSRD demonstrated relative stability, especially in shorter timeframes, compared to the other stocks.

In conclusion, the analysis demonstrates the importance of timeframes in determining trading profitability. The findings show that longer durations, such as the daily period, produce the largest returns, with KCHOL outperforming across all intervals. While XUSRD showed significant consistency in shorter durations, the overall trend showed decreasing profitability with shorter intervals, emphasising the limitations of short-term trading techniques. These findings show that long-term techniques are more advantageous, providing consistent returns while minimising the inherent dangers of high-frequency trading. This study gives useful insights into optimising trading methods by aligning them with appropriate timeframes, allowing for educated decision-making in changing market settings.

5. Conclusion and Policy Implications

The use of AI in economic forecasting has become an integral part of recent dynamic and sophisticated capital markets. By integrating indicators such as RSI, EMA, and refining strategies through backtesting and parameter adjustments, AT can outperform individual indicators, delivering outstanding results in the Turkish stock market.

The study highlights the effectiveness of combining indicators to generate more accurate and reliable trading signals, achieving the highest profitability levels on day period. The trading method used in this paper delivers outstanding performance, even with a limited amount of training data. It is suitable for high-frequency and even ultra-high-frequency trading, enabling multiple trades within a single trading day. By making predictions for individual stocks in under 30 minutes, the system cannot efficiently exploit short-term price fluctuations to seize frequent trading opportunities. This trend indicates that shorter-term trades generally result in limited returns, whereas daily, long-term trades tend to yield more favorable outcomes.

AT traders should utilize a diverse set of metrics in order to make informed decisions and gain deeper market insights. By carefully selecting and balancing these indicators, combination strategies can be further refined. It is essential to optimize and backtest strategies extensively before deploying them in live markets to identify the most effective AT methods. While the algorithm performs strongly in long term trades, its performance is somewhat affected under short-term conditions. Generally, the paper demonstrates how integrating indicators in AT helps enhance the accuracy and depth of trend predictions via their advanced data processing and predictive capabilities. Hence, AT can identify subtle patterns in data that signal potential risks or opportunities, offering early warnings to investors and policymakers.

This study has several limitations. First, the technical indicators used to develop the robotic trading method were selected randomly, and the results might differ if more or highly significant indicators were included. Second, employing alternative algorithms could potentially enhance trade timing and overall performance. Third, the system training time takes approximately 10 minutes per share that may affect real-time trading activities. Fourth, the analysis focused exclusively on large Turkish stocks listed on the BIST market, which may introduce bias. To address this, future research should apply the trading system to diverse markets, such as

NASDAQ, NIKKEI, and DOW JONES, to evaluate its broader applicability and effectiveness. Also, future studies can enhance AT by incorporating additional indicators and developing new strategies to boost accuracy and efficiency.

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