AMERICAN JOURNAL OF FINANCIAL TECHNOLOGY AND INNOVATION (AJFTI)

VOLUME 2 ISSUE 1 (2024)

PUBLISHED BY
E-PALLI PUBLISHERS, DELAWARE, USA

American Journal of Financial Technology and Innovation (AJFTI)

Volume 2 Issue 1, Year 2024
ISSN: 2996-0975 (Online)
https://doi.org/10.54536/ajfti.v2i1.2354
https://journals.e-palli.com/home/index.php/ajfti

Review of Recent Research Directions and Practical Implementation of Low-Frequency Algorithmic Trading

Talal Al-Sulaiman[1*]

Article Information

Received: January 22, 2024

Accepted: February 24, 2024

Published: February 26, 2024

Keywords

Financial Trading, Algorithms, Low Frequency, Practical Implementation, Technology

ABSTRACT

Financial trading has undergone substantial technological evolution, with automation taking center stage, leading to approximately 80% of US market trades being executed by computer systems, predominantly by large financial institutions. The rise of algorithmic trading, poised to engage smaller entities, international markets, and individual traders, drives this article's exploration of research in this field. Providing a comprehensive overview, it outlines the evolution of trading practices and defines algorithmic trading as a computer-powered tool aiding investment decisions. The article details the steps involved in algorithmic trading, covering opportunity identification, quantitative research, implementation, testing phases, and continuous monitoring. It also examines prevalent programming languages and open-source platforms facilitating algorithm development. Focusing on trading frequencies across financial instruments, it delves into high-frequency trading as a subset, alongside methodologies like technical and fundamental analysis, time series analysis, option trading strategies, and machine learning techniques used in algorithm creation. Categorized by trading frequencies, analytical approaches, involved financial instruments, and analysis objectives, the reviewed papers contribute insights into algorithmic trading's diverse landscape and methodologies, offering valuable perspectives for industry participants and researchers alike.

INTRODUCTION

As in most life aspects, technology has tremendously advanced financial systems. It includes many financial systems such as credit business, real estate, insurance, and financial markets. This advancement motivates more quantitative financial mathematics, financial engineering, actuarial science, and risk management.

This paper focuses on the evolution of trading in financial markets. Overseas business growth during the industrial revolution at the beginning of the 17^{th} inspired joint-stock companies and the Dutch East India Co. to issue the first paper shares. The paper shares make it very convenient to transfer the stocks' ownership, increasing the issue of paper shares rapidly. The place where the buyers and sellers gathered to trade the paper shares is called the stock exchange, and the first established exchange was the Amsterdam Stock Exchange (Braudel & Reynolds, 1983). The worldwide exchanges continued until the 90s of the previous century when it shifted to electronic trading (Johnson, 2014). The shift quickly increases the trading volume. However, with the increase of computational power and cloud service availability, the middle of the first decade of this century promoted computers to perform trading on behalf of individuals. It allows for automated trading to be achieved through a finite sequence of steps algorithms.

As of 2020, 80% of the trading volume is effectuated through algorithms, and most hedge funds use algorithms to set up their trading strategies. H. Simon (Simon, 1955) prevents declare the bounded rationality the human from making rational decisions due to human emotions, the mind's cognitive limitations, and time availability. Algorithmic trading (AT) allows for reducing the limitation on rationality. Algorithmic tradings have advantages over discretionary trading by removing emotions and coming up with consistent decisions. In addition, it can monitor the mark*et al*l the time and implement back testing to ensure the strategy's effectiveness. However, the algorithmic trading results depend on the quality of the developed model and its ability to capture the right signals. In other words, the algorithmic is superior to discretionary trading only if the algorithm itself besteads the discretionary traders.

However, the main advantage of AT, according to Johnson (Simon, 1955), are its ability to minimize the effect of emotions, back testing, maintain discipline and consistency, improve placing order speed, and diversification. How- ever, he stated that the main disadvantages of AT centers with the possibility of expense increase and machine failure.

The area of algorithmic trading requires multidisciplinary knowledge and skills in finance, mathematics, engineering, and programming. Algorithmic trading is usually executed through automated trading, Robot trading, and black box (Kissell, 2013).

The paper proceeds as follows: in Section 2, we defined and characterized algorithmic trading. Section 3 surveys the programming languages and platforms to research algorithmic trading. Section 4 demonstrates the domains of algorithmic trading. Section 5 shows the matrix of performance measures for backtesting. Section 6 explores the main methods used to develop an algorithm for trading. Section 7 survey-related search on various domains. Finally, Section? Provides the conclusion remarks.

[1] Audi Real Estate Refinancing Company and Engineering Management Department, Prince Sultan University, Riyadh, Saudi Arabia
[*] Corresponding author's e-mail: talalsulaiman510@outlook.com

LITERATURE REVIEW

The definition of algorithmic trading (AT) and high-frequency trading (HFT) varies among researchers. Jarnecic *et al.* (Jarnecic & Snape, 2010) define AT as computer algorithms executing predetermined trading decisions to minimize price impact. Domowitz (Domowitz & Yegerman, 2005) characterizes it as automated equity order execution via direct market-access channels. Hendershott *et al.* (Hendershott *et al.*, 2011) describe AT as using algorithms for automatic trading decisions, order submissions, and management. HFT, a primary type of AT, relies on speed for profits. Jarnecic *et al.* (Jarnecic & Snape, 2010) define HFT as high-speed algorithms generating and executing trades for capital returns. Cvitani *et al.* (Cvitanic & Kirilenko, 2010) define it as rapid, automated programs creating, directing, and executing orders in electronic markets, engaging in substantial order submissions and cancellations. Gomber *et al.* (Gomber & Haferkorn, 2015) highlight typical AT and HFT characteristics involving pre-designated decisions, live market data observation, and automated order submission and management. However, HFT differs with numerous orders and cancellations, profiting as a middleman and holding assets briefly.

The development of HFT is chiefly by financial institutions, emphasizing algorithmic trading's researcher development and implementation for retail investors. Choosing between buying or building trading software presents trade-offs. Johnson (Johnson, 2020) notes that buying existing software offers easy implementation and customization but can be costly and potentially contain loopholes. Building software, although time-consuming, offers control and customization. Numerous references like "Learn Algorithmic Trading" (Donadio & Ghosh, 2019), "Hands-On Machine Learning for Algorithmic Trading" (Jansen, 2018), "Trading Evolved" (Clenow, 2019), and "Algorithmic Trading" (Johnson, 2020) provide valuable hands-on experience in developing trading systems. Open-source trading platforms like Quantopian, Quant-Connect, and Quant-Insti provide cloud-based services for algorithm development, back-testing, and live trading (Cohan; QuantConnec Profile, 2011; Oberoi).

Algorithmic strategies' domains are crucial, as strategies may perform differently based on financial instrument types or trading environments. Derivatives like forwards, futures, swaps, and options can impact trading strategy effectiveness (Hull, 2003). Back-testing using historical data is vital to evaluate algorithm performance. Various performance measures such as portfolio diversification, concentration, and risk-return ratios (Markowitz, 1952) help assess algorithm reliability and effectiveness.

Materials and Methods

Financial markets employ technical analysis, a tool reliant on historical prices to predict market patterns and facilitate trading decisions. Originating from Charles Dow's Dow Theory in 1900 (Achelis), it focuses on interpreting price movements through charts. The analysis mainly revolves around momentum and mean reversion strategies. Momentum strategies advocate following existing trends, assuming their continuation, whereas mean reversion anticipates securities returning to their average prices. Various technical indicators, such as moving averages (MA), exponential moving averages (EMA), and Bollinger Bands (BB), aid in analyzing market trends. For example, the Double Exponential Moving Average (DEMA) utilizes two EMAs for mean reversion signals, while Bollinger Bands offer confidence intervals depicting potential overbought or oversold situations for both strategies. However, technical analysis lacks adaptiveness and learning capabilities. Integrating modern algorithms like machine learning enhances pattern detection and prediction capabilities.

Contrarily, fundamental analysis estimates assets' intrinsic value based on financial statements and economic factors, evading the Efficient Market Hypothesis (Fama, 1970). Techniques include financial ratios, discounted dividends, or free cash flow models (Graham & Dodd, 2008). Financial time series analysis evaluates and predicts security prices over time, including linear (AR, MA, ARMA, ARIMA) and nonlinear models (Threshold AR, Markov Switching AR). Volatility prediction models like ARCH and GARCH forecast variations in asset returns due to changing volatility. Moreover, computational mathematics, involving AI, machine learning, and data mining, supports these analyses (Overby, 2011; McMillan, 2002; Kastenholz, 2019). Decision trees (e.g., CART, C4.5) merge fundamental analysis with decision-making, offering actionable rules for stock actions (Rokach, 2014; Larose & Larose, 2014). These methods complement each other, enhancing market understanding and trading strategies (Box *et al.*, 2011; Tsay, 2005; Tsay, 2013).

Furthermore, the evolution of algorithmic trading is significantly influenced by advancements in neural networks, particularly Long Short-Term Memory (LSTM) networks introduced by Hochreiter and Schmidhuber (Hochreiter & Schmidhuber, 1997). LSTM, a form of recurrent neural network (RNN), features context neurons representing short-term memory dynamically updating during a time sequence. Differing from feed-forward neural networks, RNNs transmit output from context nodes back to hidden layers, involving input and forget gates, and output gate mechanisms. Weight optimization in LSTM employs backward training methods like back-propagation, resilient-propagation, and genetic algorithms. Reinforcement learning, another AI branch, aims to maximize reward through iterative actions based on observed states, as described by Q learning. Studies explore AI-driven trading strategies, from pair-switching approaches (Maewal & Bock, 2011) and technical indicator-based decision support systems (Dash & Dash, 2016; Henrique *et al.*, 2018) to employing machine learning like deep learning neural networks (Gao & Chai, 2018; Yu & Yan, 2020) and sentiment analysis (Bernile & Lyandres, 2011; Putra & Kosala, 2011). Various other strategies underline the diversity and complexity of algorithmic trading models, ranging from leveraging historical market data to predicting stock trends and exploiting market anomalies (Cohen *et al.*, 2010; Gerlein *et al.*, 2016; Kishore *et al.*, 2008; Nair *et al.*, 2010).

RESULTS AND DISCUSSION

On stock options weekly or based on options covered by the underlying assets of stocks with monthly data. Table 1 shows the most common domains of algorithmic strategies.

Table 1: Common domains of algorithmic strategies

Underlying asset	**Derivatives**	**Trading frequency**
Equity	Forward	Fractions of second
Commodity	futures	Seconds
Bonds	Options	Minutes
Foreign currency	Swap	Days
REIT	ETF	Weeks
Cryptocurrencies	Mutual funds	Months
		Years

Trend indicators attempt to detect a trend in the prices of the assets. Calculating the moving average is a common procedure to identify the up or down trends by smoothing the prices. The momentum See section 6.2 indicators estimate the speed in the changes of prices in a given time-space. The volatility indicators focus on the trading activities, possible range, and security risk. Finally, the volume indicators measure the attraction of financial assets. Table 2 shows a comprehensive classification of the technical indicators.

Table 2: Comprehensive classification of technical indicators

Trend indicators	Accumulative swing index (ASI)	Andrews pitchfork	Aroon	Detrended price oscillator
	Directional movement	Double exponential moving average	Dow theeory	Elliott wave theory
	Exponential moving average (EMA)	Fourier transform	Gann angles	Inertia
	Linear regression indicator	Mass Index	Mesa sine wave	Moving average convergence divergence (MACD)
	Parabolic stop and reverse (Parabolic SAR)	Simple moving average (SMA)	Triangular moving average (TMA)	Variable moving average (VMA)
	Weighted moving average (WMA)	Price channel	Qstick	Raff regression channel
	Speed resistance lines	Swing Index	Triple exponential moving average (TEMA)	Trend lines
	Vertical horizontal filter (VHF)	Wilder's smoothing		
Momentum indicators	Absolute breadth index (ABI)	Accumulation/ distribution line	Advance/decline ratios	Advancing declining issues
	Advancing, declining, unchanged volume	Bradth thrust	Chande momentum oscillator	Commodity channel index (CCI)
	Commodity channel Index	Commodity selection index	Dynamic momountom index	Ease of movement
	Forecast Oscillator (FO)	Intaday momountom index	McClellan oscillator	McClellan summation index
	Member short ratio	Momentum	Money flow index	New highs-lows cumulative
	New highs-lows ratio	Price oscillator	Price-rate-of-change (ROC)	Projection oscillator

	Relative momountom index	Relative strength Index (RSI)	Stochastic momentum index	Stochastic oscillator (SO)
	TRIX	Williams accumulation / distribution	Williams %R	
Volatility Indicators	Average true range	Bollinger bands	Envelopes (trading bands)	Fibonacci
	Standard deviation	TRIN arms index	Open-10 TRIN	Relative volatility index
	Standard deviation	Standard deviation channel	Standard error bands	Standard error channel
	Ultimate oscillator	Volatility Chaikin's		
Volume Indicators	Market facilitation index	Negative volume index	On balance volume	Positive volume index
	Price and volume trend	STIX	Trade volume index	upside/downside ratio
	upside/downside volume	Volume	Volume oscillator (VO)	Volume rate of change
	Volume adjusted moving average (VAMA)			
Other	Japanese candlestick	Kagi	Large block ratio	ODD lot balance index
	ODD lot short ratio	ODD proability cones	Overbought/ oversold	Public short ratio
	Put/call ratio	Random walk index	Renko	Spreads
	Three line break	Time series forecast	Tirone levels	Total short ratio
	Typical price	Weighted close	Zig zag	

A single firm's outputs should be compared to other issues of a similar type, such as the average of firms in the same sector or the average of leading firms in a similar business. Furthermore, the analyst should not look to a single period to assess the firm's quality but instead see the ratios trending over multiple periods. For example, figure 5 shows the return on equity of AAPL and MSFT from 2005 to 2020. As we can see from the figure, both companies were exposed to a drop in the ROE between 2010 and 2013. However, starting in 2017, we can see the ROE trending upward.

Table 3: Financial ratios

Liquidity ratios		
Current	Higher values are preferred	Current assets/Current liabilities
Quick	Higher values are preferred	Current assets−Inventories/Current liabilities
Inventory turnover	Higher values are preferred	Sales/Inventories
DSO	Lower values are preferred	Receivable/Daily sales
Fixed assets turnover	Higher values are preferred	Sales/Net fixed assets
Total assets turnover	Higher values are preferred	Sales/Total assets
Debt management ratios		
Debt ratio	Lower values are preferred	Total liabilities/Total assets
TIE	Lower values are preferred	EBIT/Interest charges
EBITDA coverage	Lower values are preferred	EBITDA+LP/Interest+PP +LP
Profitability ratios		
Profit margin on sales	Higher values are proffered	NIS/Sales
BEP	Higher values are preferred	EBIT/Total assets
ROA	Higher values are preferred	NIS/Total assets

ROE	Higher values are preferred	NIS/Common equity
Market value ratios		
P/E	High value indicates overpricing	Price per share/Earning per share
Price/cash flow	High value indicates overpricing	Price per share/Cashflowpershare
Market/book	High value implies high expectations	Market price per share/Book value per share

They analyze the algorithms with k = 10 before and after transaction costs on the stocks of the S&P 500 for the period from Dec 1989 to Oct 2015 using various performance measures. Table 4 shows the comparative results after transaction costs obtained by (Krauss *et al.*, 2017).

In a similar design, Fisher and Krauss (Fischer & Krauss, 2018) utilized the LSTM type of deep learning networks to compare the results of LSTM with a set of benchmarked memoryless models such as RF, deep neural network (DNN), and logistic regression (LOG). Table 5 shows the comparative results after transaction costs obtained by (Fischer & Krauss, 2018), where LSTM performs superior to the benchmarks models.

Table 4: Comparison of results obtained by Krauss *et al.* (Krauss *et al.*, 2017)

	Before transaction costs				**After transaction costs**			
	DNN	**GBT**	**RAF**	**ENS**	**DNN**	**GBT**	**RAF**	**ENS**
Daily mean return (long)	0.0033	0.0037	0.0043	0.0045	0.0013	0.0017	0.0023	0.0025
Daily mean return (short)	-0.0011	-0.0013	-0.0013	-0.0015	-0.0001	-0.0003	-0.0003	-0.0005
Daily mean return	0.0022	0.0025	0.003	0.0029	0.0012	0.0015	0.002	0.0019
Standard dev.	0.0269	0.0217	0.0208	0.0239	0.0269	0.0217	0.0208	0.0239

Table 5: Comparison of results obtained by Fisher and Krauss (Fischer & Krauss, 2018)

	Before transaction costs				**After transaction costs**			
	LSTM	**RAF**	**DNN**	**LOG**	**LSTM**	**RAF**	**DNN**	**LOG**
Daily mean return (long)	0.0029	0.003	0.0022	0.0021	0.0019	0.002	0.0012	0.0011
Daily mean return (short)	0.0017	0.0012	0.001	0.0005	0.0007	0.0002	0.0	-0.0005
Daily mean return	0.0046	0.0043	0.0032	0.0026	0.0007	0.0002	0.0012	-0.0005
Standard dev.	0.0209	0.0215	0.0262	0.0269	0.0209	0.0215	0.0262	0.0269
Max. drawdown on daily basis	0.466	0.3187	0.5594	0.5595	0.5233	0.7334	0.9162	0.9884
Annualized mean return	2.0127	1.7749	1.061	0.7721	0.8229	0.6787	0.246	0.0711
Annulaized sharpe ratio	10.0224	9.5594	4.2029	2.9614	2.3365	1.8657	0.5159	0.1024

Table 6: Comparison of results obtained by Kroencke (Kroencke *et al.*, 2014)

	Mean returns	**standard deviation**	**Sharpe ratio**
Global bonds	4.21	5.38	0.78
Global Stocks	5.81	14.31	0.41
FX carry trade	6.18	7.5	0.82
FX momentum	5.34	7.68	0.7
FX value	4.18	6.69	0.62
FX composite	8.23	7.22	1.14

The value strategy fundamentally values the currency, long undervalued, and short overvalued, assuming they will revert to their fundamental value. In addition, they developed a compounded strategy that composites the three strategies as a single trading strategy. The portfolio is balanced monthly, and the results are compared to a benchmark of global bonds and stocks. The results exhibit a superior performance of the composite strategy, as shown in table 6.

The model of Fernandez *et al.* (Fernandez-Perez *et al.*, 2018) takes advantage of the skewness anomaly in the commodities' future returns. The algorithm has a long commodity future of negative skew and a short commodity future of positive skew. Zaremba *et al.* (Zaremba *et al.*, 2019) analyze 15 commodity factors from 1986 to 2017 to find if the momentum effect exists.

The results confirm the assumption that buying a commodity with the highest past returns or selling a commodity with the lowest past returns supplement a significant profit.

Table 7: Research considerations

Objective	
Prediction	(Dash & Dash, 2016; Henrique *et al*., 2018; Gao & Chai, 2018; Yu & Yan, 2020; Al-Sulaiman, 2022; Nair *et al*., 2010; Chen & Hao, 2017; Weng *et al*., 2018; Lee *et al*., 2019; Madan *et al*., 2015; Deng *et al*., 2016; Almahdi & Yang, 2017; Al-Sulaiman, 2022; Jang & Lee, 2017; McNally *et al*., 2018; Alessandretti *et al*., 2018; Colianni *et al*., 2015; Al-Sulaiman & Al-Matouq, 2021; de Almeida *et al*., 2018)
Profit from stylized anomaly	(Maewal & Bock, 2011; Krauss *et al*., 2017; Fischer & Krauss, 2018; Gatev *et al*., 2006; Chen *et al*., 2019; Rad *et al*., 2016; Bernile & Lyandres, 2011; Dimic *et al*., 2018; Geyer-Klingeberg *et al*., 2018; Berkowitz & Depken, 2018; Lev & Nissim, 2006; Cohen *et al*., 2010; Frazzini & Pedersen, 2014; Kishore *et al*., 2008; Liu *et al*., 2003; Sadka, 2006; Garfinkel & Sokobin, 2006; Chordia & Shivakumar, 2006; Frazzini & Lamont, 2007; Faber, 2007; Faber, 2010; Lisauskas, 2011; Maze, 2012; Kroencke *et al*., 2014; Cenedese *et al*., 2012; Barroso & Santa-Clara, 2015; Baker & Haugen, 2012; Fernandez-Perez *et al*., 2018; Zaremba *et al*., 2019)
Financial instruments	
Stocks	Maewal & Bock, 2011; Dash & Dash, 2016; Henrique *et al*., 2018; Deng *et al*., 2016; Deng *et al*., 2016; Gao & Chai, 2018; Gatev *et al*., 2006; Chen *et al*., 2019; Rad *et al*., 2016; Yu & Yan, 2020; Bernile & Lyandres, 2011; Dimic *et al*., 2018; Berkowitz & Depken, 2018; Geyer-Klingeberg *et al*., 2018; Lev & Nissim, 2006; Al-Sulaiman, 2022; Cohen *et al*., 2010; Frazzini & Pedersen, 2014; Kishore *et al*., 2008; Liu *et al*., 2003; Sadka, 2006; Garfinkel & Sokobin, 2006; Chordia & Shivakumar, 2006; Nair *et al*., 2010; Chen & Hao, 2017; Weng *et al*., 2018; Lee *et al*., 2019; Frazzini & Lamont, 2007; Faber, 2007; Lisauskas, 2011; Al-Sulaiman & Al-Matouq, 2021)
Bonds	(Maewal & Bock, 2011; Faber, 2007)
FX	(Kroencke *et al*., 2014; Cenedese *et al*., 2012; Barroso & Santa-Clara, 2015; de Almeida *et al*., 2018)
Options	(Maze, 2012; Baker & Haugen, 2012)
Commodity futures	(Fernandez-Perez *et al*., 2018; Zaremba *et al*., 2019)
Bitcoin	(Madan *et al*., 2015; Jang & Lee, 2017; McNally *et al*., 2018; Alessandretti *et al*., 2018; Colianni *et al*., 2015)
Resolution	
Daily	(Dash & Dash, 2016; Henrique *et al*., 2018; Krauss *et al*., 2017; Deng *et al*., 2016; Gao & Chai, 2018; Gatev *et al*., 2006; Chen *et al*., 2019; Rad *et al*., 2016; Yu & Yan, 2020; Bernile & Lyandres, 2011; Dimic *et al*., 2018; Berkowitz & Depken, 2018; Geyer-Klingeberg *et al*., 2018; Al-Sulaiman, 2022; Liu *et al*., 2003; Sadka, 2006; Garfinkel & Sokobin, 2006; Chordia & Shivakumar, 2006; Nair *et al*., 2010; Chen & Hao, 2017; Weng *et al*., 2018; Lee *et al*., 2019; Deng *et al*., 2016; Almahdi & Yang, 2017; Barroso & Santa-Clara, 2015; Madan *et al*., 2015; Jang & Lee, 2017; McNally *et al*., 2018; Alessandretti *et al*., 2018; Colianni *et al*., 2015; Al-Sulaiman & Al-Matouq, 2021; de Almeida *et al*., 2018)
Monthly	(Frazzini & Pedersen, 2014; Faber, 2007; Engle, 1982; Lisauskas, 2011; Maze, 2012; Kroencke *et al*., 2014; Cenedese *et al*., 2012; Baker & Haugen, 2012; Fernandez-Perez *et al*., 2018; Zaremba *et al*., 2019)
Quarterly	(Maewal & Bock, 2011; Cohen *et al*., 2010; Frazzini & Pedersen, 2014; Kishore *et al*., 2008)
Yearly	(Lev & Nissim, 2006)
Methods	
Pair trading and statistical arbitrage	(Gatev *et al*., 2006; Chen *et al*., 2019; Rad *et al*., 2016; Bernile & Lyandres, 2011; Dimic *et al*., 2018; Berkowitz & Depken, 2018; Geyer-Klingeberg *et al*., 2018; Fernandez-Perez *et al*., 2018)
Fundamental Methods	(Lev & Nissim, 2006; Cohen *et al*., 2010; Frazzini & Pedersen, 2014)
Momentum	(Kishore *et al*., 2008; Liu *et al*., 2003; Sadka, 2006; Garfinkel & Sokobin, 2006; Chordia & Shivakumar, 2006; Frazzini & Pedersen, 2014; Zaremba *et al*., 2019)

AI-ML methods (LSTM, ANNT, RL, CF and GA)	(Dash & Dash, 2016; Krauss *et al.*, 2017; Deng *et al.*, 2016; Gao & Chai, 2018; Yu & Yan, 2020; Al-Sulaiman, 2022; Lee *et al.*, 2019; Deng *et al.*, 2016; Almahdi & Yang, 2017; Jang & Lee, 2017; Al-Sulaiman & Al-Matouq, 2021; de Almeida *et al.*, 2018)
AI-ML methods (SVM and SVR and logistic regression)	(Henrique *et al.*, 2018; Chen & Hao, 2017; Lee *et al.*, 2019; Madan *et al.*, 2015; McNally *et al.*, 2018; Alessandretti *et al.*, 2018; Colianni *et al.*, 2015; de Almeida *et al.*, 2018)
AI-ML methods (Decision tree, K-nearest, and random forest)	(Nair *et al.*, 2010; Chen & Hao, 2017; Lee *et al.*, 2019; Weng *et al.*, 2018; Madan *et al.*, 2015)

The cycle of algorithmic trading starts with an investment idea followed by quantitative research and model development. After that, the model's implementation using a programming language is needed, and then perform a back testing to measure the algorithm's performance in the past. Once we ensure the model validity, we test the algorithm's performance on the live stream using paper trading. Finally, as we are asserting the algorithm's quality, we may deploy it for live trading and monitor its performance. Figure 1 shows the cycle of algorithmic trading.

Figure 2 shows DEMA's extracted signals with $n^f = 20$ for the fast EMA and $n^s = 100$ for the slow EMA on the Google Inc. (GOOG) historical prices for the period from 2001 to 2018.

Relative strength index (RSI) is a popular momentum

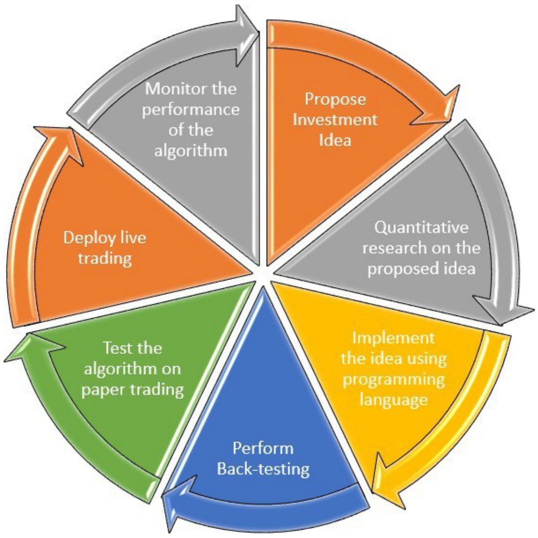


Figure 1: Cycle of algorithmic trading

Figure 2: Signal of double exponential moving average on google from 2001- 2018

indicator proposed by Welles Wilder (Wilder, 1978). The RSI compares upward and downward movements over a specific period n and returns a range of oscillator values between 0 and 100. Often, the value below 30 is an indication of oversold activities, and the value over 70 indicates overbought actions. A popular value of parameter n is n = 14, and the resolution is based on the trading frequency. In addition, n values of 9 and 25 are predominantly in use. The RSI value is determined as follows:

$$RSI = 100 - \frac{100}{\frac{\sum_{t=1}^{n} U_t}{\sum_{t=1}^{n} D_t}}$$

Where Ut and Dt are the upward and downward changes, respectively, and they following:

$U_t = \{p_t - p_{(t-1)}\ \text{if} p_t - p_{(t-1)} > 0\ 0 \text{otherwise}\ \}$

$D_t = \{|p_t - p_{(t-1)}|\ \text{if} p_t - p_{(t-1)} < 0\ 0 \text{otherwise}\ \}$

The financial statements contain considerable information about company performance divided into the balance sheet, income statement, and cash flow statement. The balance sheet provides an overlook of the assets, liabilities, and equity of the company. The income statement shows the net sales, operating costs, interest (I), taxes (T), depreciation (D) and amor- tization (A), and the earnings (E) before and after these costs (EBITDA, EBIT, EBT, net income). Finally, the cash flow statement measures the

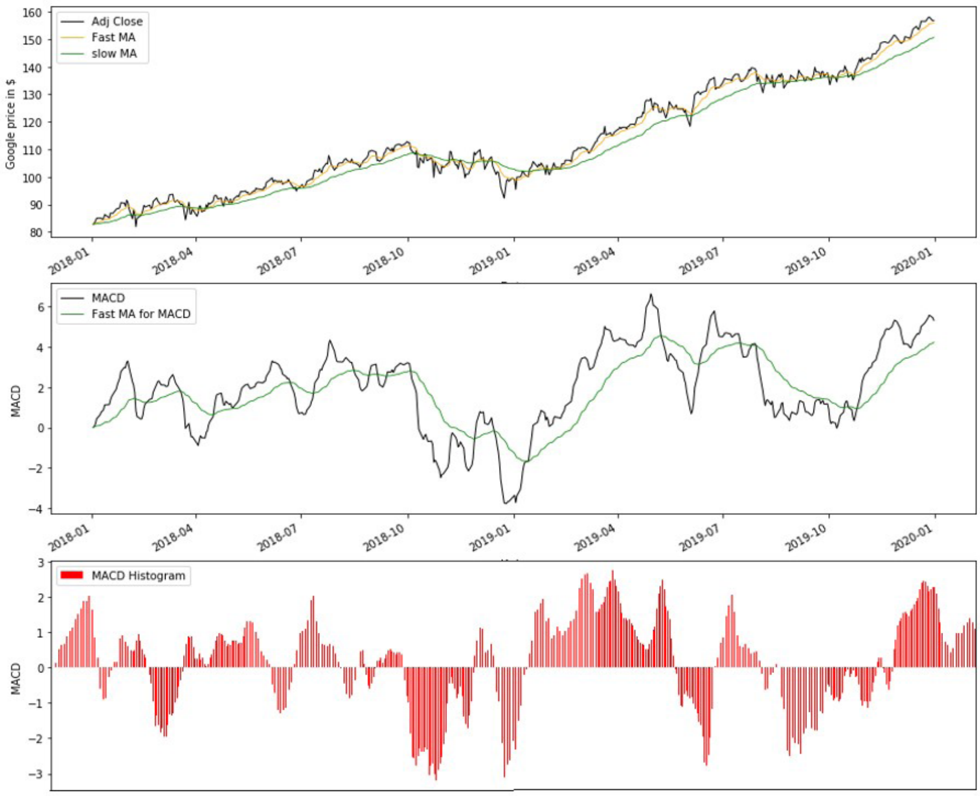


Figure 3: MACD for Microsoft from 2018-2019

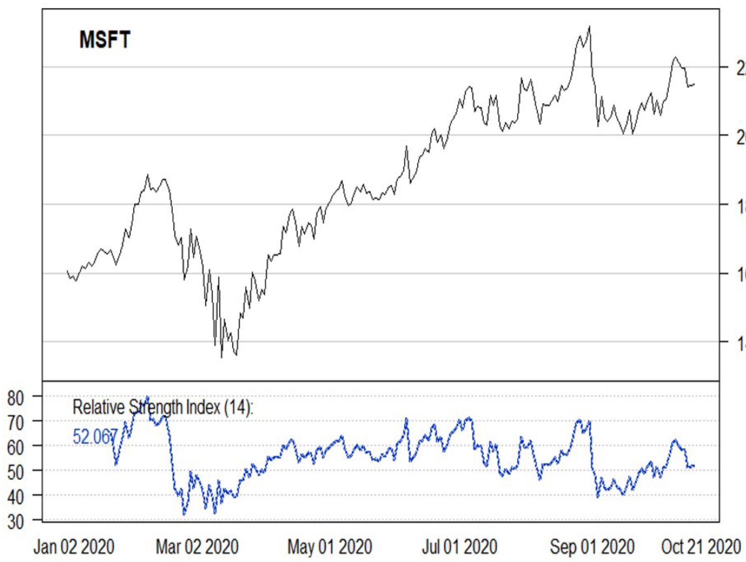


Figure 4: RSI for Microsoft for 2020

The liquidity ratio measures the firm's ability to meet its obligations. The asset management ratio identifies the efficiency of managing the in- vestment on assets compared to sales revenue. The debt management ratios aim to measure the firm's exposure to financial leverage. Profitability ratios measure the effects of the other class ratio on the operating income. Table 3 shows common ratios in each class[5].

Figure 6 shows the co-movement of Home Depo. (HD) and Wall-Mart (WMT) along with the normalized spread with trading signal given $\Delta = 1$. For more on statistical arbitrage pairs trading strategies, see (Krauss, 2017).

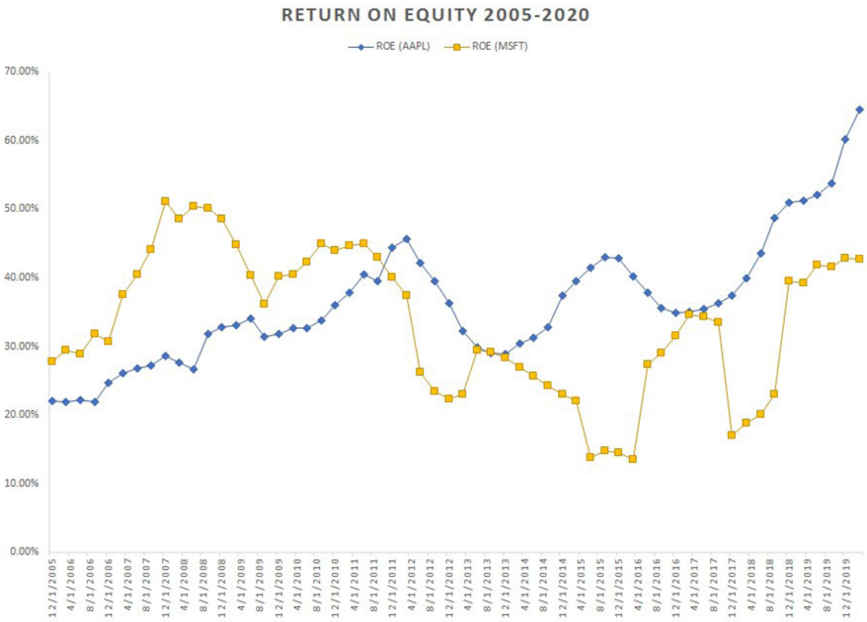


Figure 5: Return on equity from 2005 to 2020 for AAPL and MSFT

Figure 6: Signal for sample pair trading

Figure 7 shows the profits of the options strategies over a variety of possible prices at maturity.

TIn this paper, we do not aim to define, classify, differentiate or illustrate the methods in these areas, but alternatively, we focus on their application in trading and explore some of the standard methods used to develop algorithms for trading. However, machine learning and data mining algorithms aim to solve estimations, predictions, classifications, associations, and clustering problems. The problems can be classified into supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. This paper discusses the decision tree methods, the long short-term memory neural network, and reinforcement Q-learning. Nevertheless, figure 8 shows a social network of the universal methods of machine learning used in algorithmic tradings.

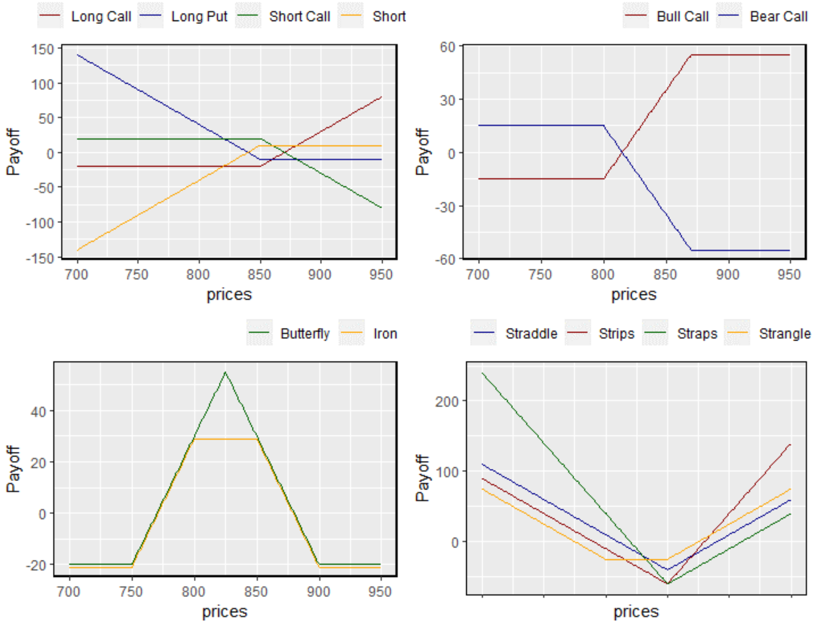


Figure 7: Possible Profits of various option strategies

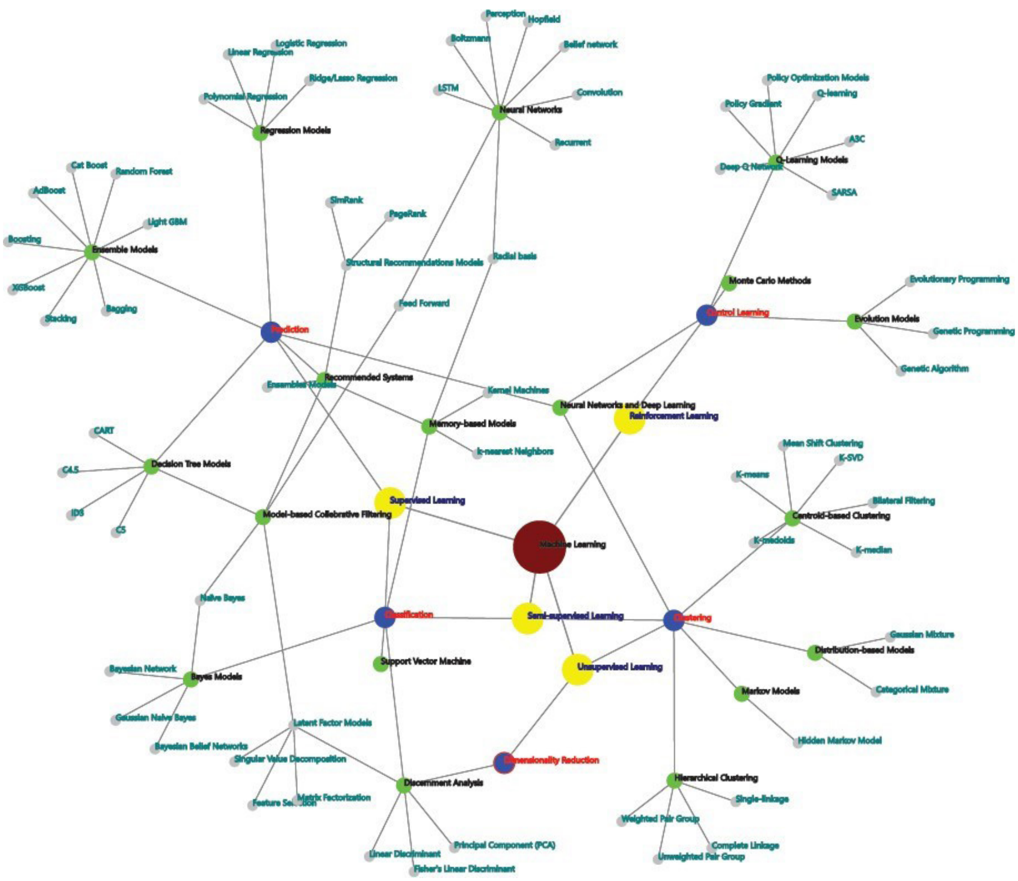
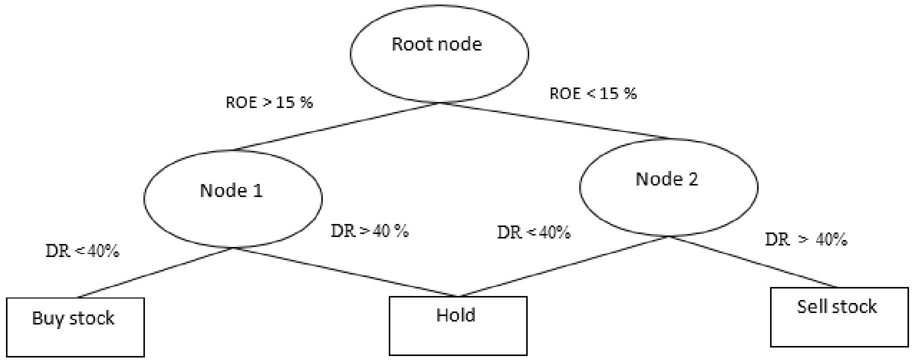


Figure 8: Social network of machine learning methods

Figure 9 shows an example of simplified decision tree rules.

The rules are achieved through constructing a path for the tree, starting the root node to leaves through the branches of decision nodes. The classification and regression algorithm (CART) is a classical decision tree algorithm. CART partitions the tree in a binary manner by splitting the tree into two branches at each decision node. The splitting is based on the maximum value of the optimality measure function among all possible split candidates.

Similar arguments apply to all the nodes in all hidden layers and the output layer. For example, figure 10 illustrates the forward path of a simplified LSTM consist of three input nodes, three nodes in the first hidden layer, two nodes in the second hidden layer, and one output node.



1. If ROE > 15% AND DR < 40% then Buy the stock
2. If ROE < 15% AND DR < 40% OR ROE > 15% AND DR > 40% then Hold
3. If ROE < 15% AND DR > 40% then Sell the stock

Figure 9: Example of decision tree rules

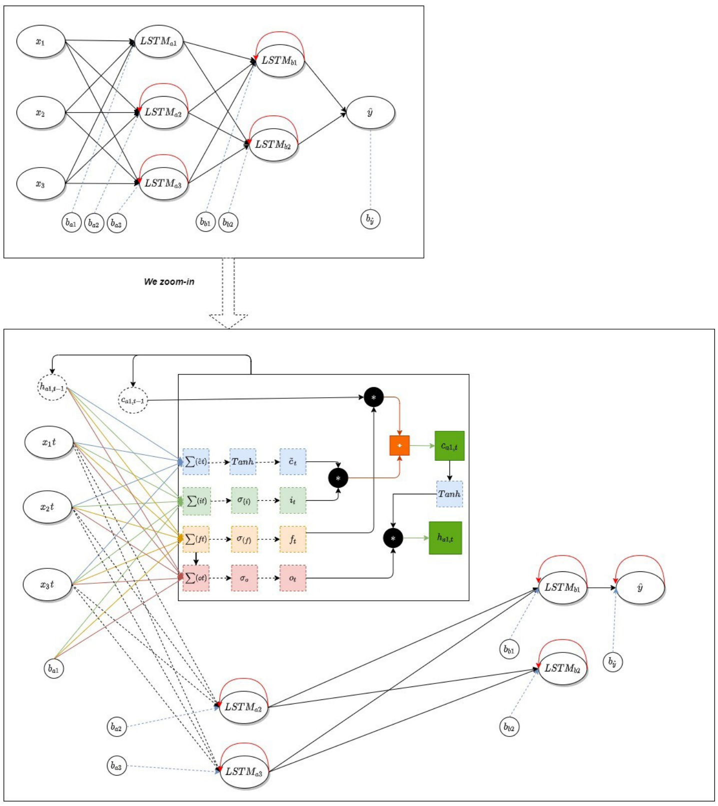


Figure 10: Illustration of LSTM neural network

CONCLUSION

In conclusion, the dominance of computer-based auto trading, representing 80% of Wall Street activity, is poised to extend to individual investors. This research comprehensively reviews algorithmic trading, encompassing definitions, project life cycles, platforms, languages, strategy classification, performance measures, and development methodologies. Primarily focusing on lower-frequency trading, it categorizes reviewed papers by objectives, financial instruments, trading periods, and methodologies. The findings highlight a focus on shorter investment periods for popular assets like stocks, with limited attention to derivatives due to complexity. Serving as a valuable resource, this paper also charts a course for future research in algorithmic trading.

REFERENCES

Al-Sulaiman, T., & Al-Matouq, A. (2021). A convex collaborative filtering framework for global market return prediction. *IEEE Access, 9*, 29458–29469.

Al-Sulaiman, T., & Yang, S. Y. (2017). An adaptive portfolio trading system: A risk-return portfolio optimization using recurrent reinforcement learning with expected maximum drawdown. *Expert Systems with Applications, 87*, 267–279.

Achelis, S. B. (n.d.). Technical analysis from A to Z.

Alessandretti, L., ElBahrawy, A., Aiello, L. M., & Baronchelli, A. (2018). Anticipating cryptocurrency prices using machine learning. *Complexity, 2018*, 2018.

Bailey, D. H., & Lopez de Prado, M. (2012). The Sharpe ratio efficient frontier. *Journal of Risk, 15*(2), 13.

Baker, N. L., & Haugen, R. A. (2012). Low risk stocks outperform within all observable markets of the world. Available at SSRN 2055431.

Barroso, P., & Santa-Clara, P. (2015). Beyond the carry trade: Optimal currency portfolios. *Journal of Financial and Quantitative Analysis, 50*(5), 1037–1056.

Berkowitz, J. P., & Depken, C. A. (2018). A rational asymmetric reaction to news: Evidence from English football clubs. *Review of Quantitative Finance and Accounting, 51*(2), 347–374.

Bernile, G., & Lyandres, E. (2011). Understanding investor sentiment: The case of soccer. *Financial Management, 40*(2), 357–380.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307–327.

Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (2011). Time series analysis: Forecasting and control (Vol. 734). John Wiley & Sons.

Brigham, E. F., & Ehrhardt, M. C. (2013). Financial management: Theory & practice. Cengage Learning.

Brigham, E. F., & Houston, J. F. (2012). Fundamentals of financial management. Cengage Learning.

Bulkowski, T. N. (2012). Fundamental analysis and position trading: Evolution of a trader (Vol. 605). John Wiley & Sons.

Cenedese, G., Sarno, L., & Tsiakas, I. (2012). Average variance, average correlation and currency returns. Technical report, Working Paper, Cass Business School.

Chen, H., Chen, S., Chen, Z., & Li, F. (2019). Empirical investigation of an equity pairs trading strategy. *Management Science, 65*(1), 370–389.

Chen, Y., & Hao, Y. (2017). A feature weighted support vector machine and k-nearest neighbor algorithm for stock market indices prediction. *Expert Systems with Applications, 80*, 340–355.

Chordia, T., & Shivakumar, L. (2006). Earnings and price momentum. *Journal of Financial Economics, 80*(3), 627–656.

Cohen, A. F., Polk, C., & Silli, B. (2010). Best ideas. Available at SSRN 1364827.

Colianni, S., Rosales, S., & Signorotti, M. (2015). Algorithmic trading of cryptocurrency based on Twitter sentiment analysis. CS229 Project, 1–5.

Conlan, C. (2016). Automated Trading with R. Springer.

Coval, J. D., & Shumway, T. (2001). Expected option returns. *The Journal of Finance, 56*(3), 983–1009.

Cvitanic, J., & Kirilenko, A. A. (2010). High frequency traders and asset prices. Available at SSRN 1569067.

Dash, R., & Dash, P. K. (2016). A hybrid stock trading framework integrating technical analysis with machine learning techniques. *The Journal of Finance and Data Science, 2*(1), 42–57.

De Almeida, B. J., Neves, R. F., & Horta, N. (2018). Combining support vector machine with genetic algorithms to optimize investments in forex markets with high leverage. *Applied Soft Computing, 64*, 596–613.

Dempster, M. A. H., & Leemans, V. (2006). An automated FX trading system using adaptive reinforcement learning. *Expert Systems with Applications, 30*(3), 543–552.

Dempster, M. A. H., Payne, T. W., Romahi, Y., & Thompson, G. W. P. (2001). Computational learning techniques for intraday FX trading using popular technical indicators. *IEEE Transactions on Neural Networks, 12*(4), 744–754.

Deng, Y., Bao, F., Kong, Y., Ren, Z., & Dai, Q. (2016). Deep direct reinforcement learning for financial signal representation and trading. *IEEE Transactions on Neural Networks and Learning Systems, 28*(3), 653–664.

Deng, Y., Kong, Y., Bao, F., & Dai, Q. (2015). Sparse coding-inspired optimal trading system for HFT industry. *IEEE Transactions on Industrial Informatics, 11*(2), 467–475.

Dimic, N., Neudl, M., Orlov, V., & A¨ij¨o, J. (2018). Investor sentiment, soccer games and stock returns. *Research in International Business and Finance, 43*, 90–98.

Domowitz, I., & Yegerman, H. (2005). The cost of algorithmic trading: A first look at comparative performance. *The Journal of Trading, 1*(1), 33–42.

Donadio, S., & Ghosh, S. (2019). Learn Algorithmic Trading: Build and deploy algorithmic trading systems and strategies using Python and advanced data analysis. Packt Publishing.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, 987–1007.

Faber, M. (2010). Relative strength strategies for investing. Available at SSRN 1585517.

Faber, M. T. (2007). A quantitative approach to tactical asset allocation. *The Journal of Wealth Management, 9*(4), 69–79.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance, 25*(2), 383–417.

Fayek, M. B., El-Boghdadi, H. M., & Omran, S. M. (2013). Multi-objective optimization of technical stock market indicators using GAS. *International Journal of Computer Applications, 68*(20).

Fernandez-Perez, A., Frijns, B., Fuertes, A.-M., & Miffre, J. (2018). The skewness of commodity futures returns. *Journal of Banking & Finance, 86*, 143–158.

Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research, 270*(2), 654–669.

Fischer, T. G. (2018). Reinforcement learning in financial markets - a survey. Technical report, FAU Discussion Papers in Economics.

Frazzini, A., & Lamont, O. A. (2007). The earnings announcement premium and trading volume. Available at SSRN 986940.

Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics, 111*(1), 1–25.

Gao, T., & Chai, Y. (2018). Improving stock closing price prediction using recurrent neural network and technical indicators. *Neural Computation, 30*(10), 2833–2854.

Garfinkel, J. A., & Sokobin, J. (2006). Volume, opinion divergence, and returns: A study of post–earnings announcement drift. *Journal of Accounting Research, 44*(1), 85–112.

Gatev, E., Goetzmann, W. N., & Rouwenhorst, K. G. (2006). Pairs trading: Performance of a relative-value arbitrage rule. *The Review of Financial Studies, 19*(3), 797–827.

Georgakopoulos, H. (2015). Quantitative trading with R: Understanding mathematical and computational tools from a quant's perspective. Springer.

Gerlein, E. A., McGinnity, M., Belatreche, A., & Coleman, S. (2016). Evaluating machine learning classification for financial trading: An empirical approach. *Expert Systems with Applications, 54*, 193–207.

Geyer-Klingeberg, J., Hang, M., Walter, M., & Rathgeber, A. (2018). Do stock markets react to soccer games? A meta-regression analysis. *Applied Economics, 50*(19), 2171–2189.

Gomber, P., & Haferkorn, M. (2015). High frequency trading. In Encyclopedia of Information Science and Technology, Third Edition (pp. 1–9). IGI Global.

Graham, B., & Dodd, D. (2008). Security analysis. McGraw-Hill.

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *The Journal of Finance, 66*(1), 1–33.

Henrique, B. M., Sobreiro, V. A., & Kimura, H. (2018). Stock price prediction using support vector regression on daily and up to the minute prices. *The Journal of Finance and Data Science, 4*(3), 183–201.

Hilpisch, Y. (2020). Artificial Intelligence in Finance. O'Reilly Media, Inc.

Hilpisch, Y. (2020). Python for Algorithmic Trading: From Idea to Cloud Deployment. O'Reilly Media, Inc.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780.

Hull, J. C. (2003). Options futures and other derivatives. Pearson Education India.

Jang, H., & Lee, J. (2017). An empirical study on modeling and prediction of bitcoin prices with bayesian neural networks based on blockchain information. *IEEE Access, 6*, 5427–5437.

Jansen, S. (2018). Hands-On Machine Learning for Algorithmic Trading: Design and implement investment strategies based on smart algorithms that learn from data using Python. Packt Publishing Limited.

Jarnecic, E., & Snape, M. (2010). An analysis of trades by high frequency participants on the London Stock Exchange. Technical report, Working Paper, June.

Johnson, A. (2020). Algorithmic Trading: Tips and Tricks to Learn and Win with Algorithmic Trading. Independently published.

Johnson, A. (2020). Algorithmic Trading: Tips and Tricks to Learn and Win with Algorithmic Trading. Independently published.

Johnson, R. S. (2014). Equity markets and portfolio analysis (Vol. 618). John Wiley & Sons.

Kastenholz, M. (2019). Trading Derivatives: The Theoretical Minimum: Trading Vanilla, Exotic and Corporate Derivatives. MAK Risk.

Kishore, R., Brandt, M. W., Santa-Clara, P., & Venkatachalam, M. (2008). Earnings announcements are full of surprises. Available at SSRN 909563.

Kissell, R. L. (2013). The science of algorithmic trading and portfolio management. Academic Press.

Krauss, C. (2017). Statistical arbitrage pairs trading strategies: Review and outlook. *Journal of Economic Surveys, 31*(2), 513–545.

Krauss, C., Do, X. A., & Huck, N. (2017). Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500. *European Journal of Operational Research, 259*(2), 689–702.

Kroencke, T. A., Schindler, F., & Schrimpf, A. (2014). International diversification benefits with foreign exchange investment styles. *Review of Finance, 18*(5), 1847–1883.

Larose, D. T., & Larose, C. D. (2014). Discovering knowledge in data: An introduction to data mining (Vol. 4). John Wiley & Sons.

Lee, T. K., Cho, J. H., Kwon, D. S., & Sohn, S. Y. (2019). Global stock market investment strategies based on financial network indicators using machine learning techniques. *Expert Systems with Applications, 117*, 228–242.

Lev, B., & Nissim, D. (2006). The persistence of the accruals anomaly. *Contemporary Accounting Research, 23*(1), 193–226.

Madan, I., Saluja, S., & Zhao, A. (2015). Automated bitcoin trading via machine learning algorithms. Available at http://cs229.stanford.edu/proj2014/Isaac%20Madan.

Maewal, A., & Bock, J. R. (2011). Paired-switching for tactical portfolio allocation. Available at SSRN 1917044.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance, 7*(1), 77–91.

Maze, S. (2012). Dispersion trading in South Africa: An analysis of profitability and a strategy comparison. Available at SSRN 2398223.

McMillan, L. G. (2002). Options as a strategic investment. Penguin.

McNally, S., Roche, J., & Caton, S. (2018). Predicting the price of bitcoin using machine learning. In 2018 26th Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP) (pp. 339–343). IEEE.

Menkhoff, L., Sarno, L., Schmeling, M., & Schrimpf, A. (2012). Currency momentum strategies. *Journal of Financial Economics, 106*(3), 660–684.

Moody, J., & Saffell, M. (2001). Learning to trade via direct reinforcement. *IEEE Transactions on Neural Networks, 12*(4), 875–889.

Murphy, J. J. (1999). Technical analysis of the financial markets: A comprehensive guide to trading methods and applications. Penguin.

Nair, B. B., Mohandas, V. P., & Sakthivel, N. R. (2010). A decision tree—rough set hybrid system for stock market trend prediction. *International Journal of Computer Applications, 6*(9), 1–6.

Nazário, R. T. F., Silva, J. L. E., Sobreiro, V. A., & Kimura, H. (2017). A literature review of technical analysis on stock markets. *The Quarterly Review of Economics and Finance, 66*, 115–126.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society, 59*(2), 347–370.

Oberoi, R. (2016). Slow steady, algo trading takes up decent share on Dalal Street. The Economic Times.

Overby, B. (2011). The Options Playbook. Ally Invest.

Park, H., Kim, N., & Lee, J. (2014). Parametric models and non-parametric machine learning models for predicting option prices: Empirical comparison study over KOSPI 200 index options. *Expert Systems with Applications, 41*(11), 5227–5237.

Putra, E. F., & Kosala, R. (2011). Application of artificial neural networks to predict intraday trading signals. Binus university e-activities.

Rad, H., Low, R. K. Y., & Faff, R. (2016). The profitability of pairs trading strategies: Distance, cointegration and copula methods. *Quantitative Finance, 16*(10), 1541–1558.

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics, 80*(2), 309–349.

Schoreels, C., Logan, B., & Garibaldi, J. M. (2004). Agent based genetic algorithm employing financial technical analysis for making trading decisions using historical equity market data. In Proceedings. IEEE/WIC/ACM International Conference on Intelligent Agent Technology, 2004.(IAT 2004) (pp. 421–424). IEEE.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance, 19*(3), 425–442.

Simon, H. A. (1955). A behavioral model of rational choice. *The quarterly journal of economics, 69*(1), 99–118.

Treleaven, P., Galas, M., & Lalchand, V. (2013). Algorithmic trading review. *Communications of the ACM, 56*(11), 76–85.

Tsay, R. S. (2005). Analysis of financial time series (Vol. 543). John wiley & sons.

Tsay, R. S. (2013). Multivariate time series analysis: With R and financial applications. John Wiley & Sons.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty, 5*(4), 297–323.

Valencia, F., G´omez-Espinosa, A., & Vald´es-Aguirre, B. (2019). Price movement prediction of cryptocurrencies using sentiment analysis and machine learning. *Entropy, 21*(6), 589.

Weng, B., Lu, L., Wang, X., Megahed, F. M., & Martinez, W. (2018). Predicting short-term stock prices using ensemble methods and online data sources. *Expert Systems with Applications, 112*, 258–273.

Wilder, J. W. (1978). New concepts in technical trading systems. Trend Research.

Yu, L., Wang, S., & Lai, K. K. (2010). Foreign-exchange-rate forecasting with artificial neural networks (Vol. 107). Springer Science & Business Media.

Yu, P., & Yan, X. (2020). Stock price prediction based on deep neural networks. *Neural Computing and Applications, 32*(6), 1609–1628.

Zaremba, A., Mikutowski, M., Karathanasopoulos, A., & Osman, M. (2019). Picking winners to pick your winners: The momentum effect in commodity risk factors. *The North American Journal of Economics and Finance, 50*, 101017.